Three Essays on the Economics of Crime

by

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Abstract

This thesis analyses three research questions on the Economics of crime using econometric techniques on panel level and individual level data sets in England and Wales. Chapter one focuses on the swiftness in the justice system and its effects on crime rates. Using a unique data set for court waiting times in days in England and Wales, and utilising a fixed effects model and instrumental variable approach, we find that effects vary on what type of crime it is. Chapters two and three explore how effective non-custodial sentences can be in reducing crime and reoffending rates. In particular, chapter two focuses on alternatives to custody on four different crime categories and chapter three uses individual level data and analyses the effects of Community Resolution on the recidivism rates for first time, low level offenders. The analysis in chapter two on sentencing in England and Wales finds after controlling for socio-economic variables in each area, that alternatives to custody can be effective at reducing certain types of crime. Chapter three uses individual level data from Norfolk and Suffolk Police and finds that Community Resolution can significantly reduce reoffending rates and time to reoffending.

To a great economist and the best grandfather I could have ever wished for

Algirdas Valiauga

(1932 – 2016)

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1. Introduction

England and Wales have some of the highest incarceration rates in the developed world. Recent policy reforms have focused on developing alternatives to custody that offer credible protection for the public, and justice for victims of crime. In my three chapters I look into the effectiveness of the justice system in England and Wales, specifically into general deterrents, specific deterrents and the swiftness of the justice system. I try to contribute to the existing crime literature by exploring the effects of alternatives to custody to capture general deterrence using aggregate data and specific deterrence using individual level data. I also use aggregate data to analyse the effects of swiftness of the justice system across three crime types. My findings suggest that there are some credible alternatives to prison which can also prove to be very cost effective, that diverting away from the formal proceedings through the justice system for low level offenders where applicable can have a reducing effect on reoffending later on and that celerity of the justice system might work in a different direction to crime reduction than previous theory would suggest.

Many studies include detection and/or conviction rates to try to account for certainty of punishment. Some studies include sentencing measures to account for severity. Chapter one of this thesis makes a contribution to existing crime literature by also including court waiting times as a measure of swiftness in the justice system. From the classical 3c' theory of crime deterrence we know that if we want justice system to be an effective deterrent, we need certain punishment, which is severe enough and delivered swiftly. If the waiting times (known as celerity in crime literature) – measured in average days in waiting between a crime being committed and conviction in court – would increase, how would that affect the behaviour of the offenders? If there is no or very little supervision whilst waiting for their day in court, people might commit more crimes anticipating that if they are sentenced they might not be able to commit crimes after sentencing. However, if whilst waiting there are bail conditions imposed and additional police supervision, that might incentivise the offender to avoid further offences due to higher chances of being caught. Therefore, the overall effect of celerity is likely to depend on the surrounding factors and I suggest in my proposed hypothesis that waiting for justice can have an ambiguous effect on crime rates and it would depend not only on the future discounting of the criminals but also how waiting time is being monitored by the police which in turn would affect the probability of detection for any crimes committed while waiting.

By using crime data from 41 police force areas in England and Wales from 1994 to 2008 as well as a number of socio-economic variables to control for other factors influencing crime rates in the region, I adopt a fixed effects estimation methodology and instrument crime detection rate with various lags of police expenditure per police officer to show that longer waiting times have mixed effects on crime rates depending on what type of crime it is.

Chapter two analyses the effects of custodial and non-custodial sentences on police-recorded crime using a unique detailed panel-level data acquired from the Ministry of Justice through a *Freedom of Information* request for all Police Force Areas from 2002 to 2013 in England and Wales. This data set details the different sentences that have been issued for all crime types each year and allows one to distinguish between sentence types i.e. the number of prison sentences and non-custodial sentences such as community sentences, conditional discharge, fines and suspended sentences. The results from the empirical analysis show that prison, in some circumstances, can be effective at reducing acquisitive crime, but that alternatives to custody are also effective in many cases. Although these findings are most directly applicable to England and Wales, they have relevance to a more general understanding of criminal justice effectiveness.

Chapter three uses individual level data collected by Norfolk and Suffolk Police on case disposals to analyse the effects of Community Resolution on reoffending. Community Resolution allows the police to make decisions about how to deal more proportionately with lower level crimes and it is focused at first time offenders who showed genuine remorse, and where the victim (if there is one) has agreed that the police do not take more formal action. Since reoffending rates remain high in the UK for both adult and juvenile offenders, it is important to understand what works well at a micro level. In particular, if Community Resolution is effective, this could lead to significant savings of the public funds by police spending less time and money on investigations and processing of low level offences which in turn would allow them to focus more on serious offences. Using Propensity Score Matching and Survival Analysis on four different time intervals to reoffend, we find that Community Resolution can significantly reduce reoffending rates and time to reoffending.

2. Is Justice delayed justice denied? Exploring the impact of sanction celerity on crime

2.1 Introduction

The determinants of crime and the effectiveness of crime reduction interventions are widely discussed by the public, politicians and academics. There is a fair amount of variance in what people believe to be the reasons for criminal behaviour and most importantly the best crime reduction approaches. There is a debate between those who believe law enforcement and criminal justice processing policies play a major role while others focus on so called root causes viz. socio economic conditions. Even within those who emphasise the role of law enforcement and criminal justice processing, there is debate on the relative importance of the different factors. Lengthy prison sentences and heavier fines are proposed by some, more efficient policing in terms of detection and conviction rates are the focus of others with waiting times for the sentencing to take place or better reoffending management highlighted by yet another group of scholars and practitioners. The theory of deterrence has developed from the work of three classical philosophers Hobbes, Beccaria and Bentham (Beccaria, 1764, Bentham, 1780, Hobbes, 1996). It relies on three components, also, called *3 Cs*: Severity, Certainty and Celerity of the punishment. The severity of the punishment is believed to be one the key elements implemented by the criminal law to encourage citizens to obey the law. Also, certainty of that punishment implies that the punishment will take place if the crime is committed. Some theorists, such as Beccaria, believe that if individuals know they will be punished in a case of committing a crime, they will refrain from committing those crimes in the future. Moreover, he argues that their punishment must be swift if one wants to deter the crime. To sum up the deterrence theorists believe that if punishment is severe, certain and swift, a rational individual will measure potential gains and losses before engaging in illegal activity and will be discouraged from breaking the law if the loss is greater than the gain. Although the deterrence theory can be traced down from centuries ago, it was not tested or empirically measured much until the late 1960s. Prior to the 1960s, most studies focused mainly on the philosophical ideas rather than on empirically testing the deterrence theory.

Nowadays amongst policymakers there is a strong cross-party consensus that access to speedy justice is crucial both for reducing crime and satisfying the interests of victims. In the United Kingdom, New Labour, under the banner of Tony Blair's (in)famous slogan, 'tough on crime, tough on the causes of crime', made access to swift criminal justice a key policy priority (Morgan, 2008). One influential government strategy document promised that 'cases that need the court process will be dealt with fairly but as quickly as possible' while also suggesting wider use of 'summary' procedures including dealing with cases just a day after initial charge (Home Office, 2004, 2006). Using remarkably similar language and rationale, the Coalition Government that followed New Labour proclaimed: 'Justice needs to be swift if it is to be effective. Offenders need to be made to face the consequences of their actions quickly, using effective, locally-based solutions.' (Ministry of Justice, 2012) This intention to streamline the process bringing offenders to justice has continued under the current Conservative government (HM Treasury, 2015).

In this chapter with the help of unique panel data on the average length of time between offence and conviction received from the United Kingdom's Ministry of Justice through a *Freedom of Information* request, we contribute an additional perspective to this relatively neglected aspect of criminal justice practice and deterrence theory. We analyse the effect of length of time between a crime being committed and conviction in court. In line with previous research into celerity, we find the impact of different conviction times to be mixed. We suggest that this result is not because this factor is necessarily unimportant, but because the overall result emerges from an interplay between specific and general deterrent effects. We propose that where there is no or very little supervision while awaiting their day in court, people may commit more crime rationally anticipating that they might not be able to commit crimes after sentencing. However, delaying a sanction for a particular offender which allows for bail conditions to be imposed and additional police supervision incentivises that offender to avoid further offences at least while the sanction outcome is still to be determined. The overall effect of celerity is thus likely to depend critically on other factors including how effectively tendencies in sentencing is communicated to a general population (which contributes to a general deterrent effect), when a decision to commit an offence is a rational calculation by the offender and also depends on the (level of) certainty of detection.

2.2 The theory

Hobbes (1996) was among the first theorists to introduce the notion that conflict over resources could arise between rational self-interested individuals. Since those in conflict respond to incentives, a state with sufficient legitimacy could deter potential rebels against the peace, provide civil order, and protect productive activities such as commerce. Beccaria refined this account by introducing three components of punishment, sometimes given the moniker 'the *3 Cs'*, Severity, Certainty and Celerity (Nagin, 2013). Beccaria believed that if individuals expect to pay a greater penalty for committing a crime than not committing it, they will refrain. As a result, he was also an early advocate for criminal justice reform, arguing against torture and secret accusations not just in reaction to their inhumanity but because they failed to establish rational expectation among those subject to the laws, and hence were ineffective at controlling crime (Paternoster, 2010). Beccaria also introduced the notion of marginal deterrence, stating that "If an equal punishment be ordained for two crimes that injure society in different degrees, there is nothing to deter men from committing the greater as often as it is attended with greater advantage".

Bentham, drawing inspiration from Beccaria, linked this account to his theory of utilitarianism and thus eventually to modern economic theory. He argued that the object of law was to maximise the happiness of the people by increasing their pleasure and lessening their pain. As a result, he argued that punishment in excess of what is essential to deter people from committing illegal acts is unjustified. All these theorists believed that if punishment is sufficiently severe, certain and swift, a rational individual will measure potential gains and losses before engaging in illegal activity and will be discouraged from breaking the law if the loss is greater than the gain.

Strangely, the celerity aspect of deterrence lost its place amongst the 'three Cs' when deterrence was imported into contemporary economic theory (Nagin, 2013). Becker (1968) first applied formal economic analysis to crime in his famous crime and punishment model. In his model, the cost of the criminal act includes the probability of getting caught and the severity of the punishment. He proposed that an individual chooses an illegal activity over a legal one if his or her utility from illegal activity exceeds the utility from the legal one:

$$EU_i > EU_l$$

where EU_i is expected utility from illegal sector and EU_l is expected utility from the legal sector. Then we can define EU_i as:

$$EU_i = (1 - p) * EU(Crime) + p * EU(S)$$

where $EU(Crime)$ is expected utility from criminal activities, $EU(S)$ is expected utility from sentence if individual is caught which comes with a probability *p*. This simple form of Becker's crime model states that an individual will choose illegal sector only if his utility from illegal activities is higher than from his expected returns from legal sector. Following this model, we can see that both certainty and severity of the punishment should affect the crime rates negatively:

$$\frac{\partial EU_i}{\partial p} = -EU(Crime) + EU(S) < 0$$

$$\frac{\partial EU_i}{\partial S} = -pEU'(S) \quad < 0$$

However, we can extend this model including celerity. In other words, in a case where detection has occurred, we can look at how long would an individual have to wait for the punishment to be announced. Simple temporal discounting would suggest that the longer the waiting time between crime and punishment, the less strong the deterrent of the potential punishment. Hence, greater celerity would be expected to reduce crime. This is true, when we extend the model to look at those who are caught and conditional on being expected to be sentenced and hence face lower payoffs post-conviction from legal opportunities (convicted people face lower probability of employment in the legal sector). However, waiting times have ambiguous effects if supervision, while waiting for trial, lowers their crime opportunity.

2.3 Empirical literature

Becker's revival of deterrence theory inspired a broad range of empirical studies. One prediction of Becker's model is that increasing the severity of punishment could act as a substitute for certainty of detection. However, empirical observation suggests that different elements of deterrence have different effects. Certainty of punishment has been the most explored area and there is now a relatively strong consensus that increasing the likelihood of apprehension reduces crime (Von Hirsch et al., 1999, Bailey et al., 1974). In the United Kingdom, a number of researchers have used at the level of police force areas (PFAs) to develop panel data analyses. Witt et al. (1999) linked increasing wage inequality and more cars per capita with higher crime, but also found that a larger police force was associated with lower property crime. Machin and Meghir (2004) found that fewer opportunities for low-wage work were associated with higher acquisitive crime, and also found that potential offenders are deterred by higher conviction rates. Han et al. (2013) found a strong relationship between higher police detection rates and lower crime rates in subsequent years. Another panel study of Greek regions (Saridakis and Spengler, 2012) found that property crime was deterred by higher clear-up rates and reduced by lower unemployment, but these effects were generally insignificant for violent crime.

In the United States, several panel studies have been used to explore the effects of incarceration on crime rates (Durlauf and Nagin, 2010). The results were inconsistent, with only some studies suggesting that prison population growth had a small deterrent effect. Vieratis et al. (2007) combined panel data of prison growth and prisoner releases. They found that prison growth was associated with lower crime but that releasing prisoners was associated with higher crime, an effect they attributed to the criminogenic effects of incarceration. This suggests that the crime reduction effect of more incarceration can be short-lived, and that use of prison might be a double-edged sword that can easily prove counter-productive. A panel study comparing justice systems in German states (Spengler, 2006) found that higher conviction rates were associated with lower crime rates but not the form, or severity, of sanction. Spelman (2013) offered a more sophisticated solution to disentangling the co-dependence of crime and prisons, by finding instruments for crime that predict changes in prison population, before deriving the effects of prison on crime. His results suggest that increased use of prison was, on balance, crime reductive in the US. More recently, Bhuller et al (2016) explored effects imprisonment on recidivism with a focus on rehabilitation and further employment using a panel data containing the criminal behaviour and labour market outcomes of the entire population in Norway. They find that time spent in prison can reduce future offending if there is focus on rehabilitation improving employability which ultimately raises employment and earnings and discourages from further involvement in criminal activities.

Research designs that examine the effect of sanction on individual offenders offer a different perspective, one potentially much more critical of increasing sanction severity. An array of randomised controlled trials (RCT) have examined the effects of short periods of custody on offenders compared to alternative sentences (Killias and Villetaz, 2008). The results are not conclusive but suggest that prison for low-level offenders might have a small criminogenic effect. Existing offender characteristics were much larger predictors of criminal career prospects. RCTs have arguably the highest levels of internal validity. However, there are questions about how far these results can be extrapolated to a general population of offenders. It is rare that justice systems can permit random selection of sanctions. When they do, the offenders studied are necessarily low-level, as they have to be eligible for a community disposal. Comparatively small numbers of offenders are included in these studies with the result that real but relatively small effects might be hard to detect with certainty.

Smith et al. (2002) reviewed studies which compared the effects of community sentences with custodial sentences. They restricted their survey to those with study designs which controlled for offender characteristics and found 31 eligible studies. A small effect suggesting that prison sentences might be associated with increased recidivism was found. They concluded that variations in the kind of sentence 'did not produce decreases in recidivism' although they did find 'tentative indications that increasing lengths of incarceration were associated with slightly greater increases in recidivism'.

Nieuwbeerta et al. (2009) identified the effects of first-time incarceration on individual offenders. They used risk-matching to control for individual differences between offenders given custodial sentences compared with alternatives. They examined criminal activity 3 years following the different judicial interventions, and concluded that being incarcerated had a criminogenic effect, putting offenders on a more serious criminal career path. These matching approaches have become successively more effective at estimating the impact of differential sentencing on individual offenders, including long term impacts on criminal career trajectories. They suggest, in contrast to the modest reductions in crime associated with increased incarceration in panel data, that harsher penalties potentially increase crime.

Kessler and Levitt (1999) tested the model using California's Proposition 8 which allowed for imposing sentence enhancements for a selected number of crimes. In their paper they demonstrated that these sentence enhancements which are increases in punishment added on to prison sentences, which would have been served anyway, provide a direct means of measuring deterrence (in the population). Any changes in crime rate after these enhancements must be due to deterrence because offenders would have been sent to prison anyway so there would be no additional incapacitation effect from the sentence enhancement in the short run. They found that three years after the law was introduced, selected crimes have decreased by 20 - 40 per cent compared to non-eligible crimes.

Bandyopadhyay et al (2012) analysed the impact of sentencing on various types of crimes in England and Wales. Using data from 1993 to 2008 from all 43 Police Force Areas they found that detection has a negative and significant effect on all crime types analysed and the impact of sentences is negative and significant for only burglary and fraud.

While the evidence for the effect of certainty is strong, and the impact of severity ambiguous, the evidence on celerity is 'scant' (Nagin and Pogarsky, 2011). This is despite existing evidence that time preference exerts a critical influence, at least, on the way that offenders weight severity in terms of length of prison sentences themselves (Lee and McCrary, 2005). A cross-sectional analysis explored the popular hypothesis that delayed executions for homicide in the United States blunted the deterrent effect of the death penalty but found no significant effects (Bailey, 1980). A somewhat dated review of the evidence, of mostly laboratory experimental studies, found celerity to contribute to deterrence but not one when intervening variables were included (Clark, 1988). More recent experimental studies asked potential offenders about crime and punishment scenarios, focussed on decisions to engage in drink driving (Loughran et al., 2012, Nagin and Pogarsky, 2001). These studies suggest that anticipated celerity of sanction does influence potential offenders. However, another study of a random sample of drink driving cases processed in New York state found no effect from celerity (Yu, 1994). A more recent study used arrest data from Dallas, Texas, to study a much wider range of defendants using Propensity Score Matching method, finding that celerity of arrest was associated with significantly less recidivism (Zettler et al., 2015), although the impact of celerity diminished after 30 days. To the best of our knowledge, no study before the present one has integrated measures of celerity of conviction into a panel data analysis.

2.4 Discussion: Specific, general and prospective deterrence

A general deterrent effect is not simply an aggregation of specific deterrent activities. What makes a deterrent general is the influence it has on a whole population of potential offenders, not only those who are caught and convicted. If we assume perfect information, past personal experience of punishment should not influence an individual agent's decision to commit crime in the future. Sanctioned agents are already fully aware of the risk of punishment and, when caught, have not so much miscalculated their decision to engage in crime, but are merely unfortunate to get caught on that occasion. In this rarefied model, increased sanctions that increase the 'price' of engaging in crime have only a general deterrent impact: shifting the supply of crimes to a new lower equilibrium. The fact that individuals are caught and punished reflects that the price (of being caught and sentenced) is still perceived to be a fair bargain by some offenders and they still make a decision to engage in criminal activities.

In a more realistic scenario, potential offenders are not perfectly informed. In this context, specific deterrence plays fundamentally an informational or signalling role. It can reveal new information to offenders that they will, in fact, be caught and suffer additional penalties if they do not desist (Apel, 2013). Besides acting on the individual punished, the existence of social networks amongst criminal peers means that knowledge about the likelihood and severity of punishment can spread, albeit unsystematically, to other potential offenders (Dickinson and Wright, 2015). In the case of joint criminal enterprises, giving some potential offenders specific, prospective sanctions is associated with lower crime amongst their peers (Drago and Galbiati, 2012).

However, this learning process can also have unfortunate side-effects. An offender might perversely conclude that the penalty (for example, experiencing a community sentence or a brief prison term) was not as unpleasant as they previously expected. Their updated expectations could encourage them to commit more rather than less crime. At the same time, experience in prison may have encouraged them to build up criminal capital and lose social capital, making them 'better' criminals but less likely to find work in the legitimate economy. At the same, the process of socialisation, especially in harsh prison conditions, can make re-integration into society less likely (Drago et al., 2011).

On the other hand, we would expect the credible prospect of a future sanction to have a deterrent effect without some of these side-effects. Indeed, a number of empirical studies have identified significant behavioural effects of prospective sanctions. Drago et al. (2009) exploit a mass pardon in the Italian prison system which introduced a number of exogenous changes to a cohort of prisoners. They found that prisoners pardoned early, and so eligible for a longer sentence if reconvicted were significantly less likely to re-offend. They concluded that the prospect of prison deterred subsequent crime. The potential weakness to this particular analysis is that the prospect of a longer sentence is reverse correlated with the length of the sentence served so far (Durlauf and Nagin, 2010). This means that it is impossible to say from this method alone whether the lower level of observed offending is due to less prison experienced already or the prospect of more prison in the future. However, another study exploited variation in New South Wales' 'good behaviour bonds' to show that offenders given longer periods in which the prospect of a specific penalty remains leads to lower re-offending (Poynton et al., 2014). Special drug courts have also exploited the opportunity to suspend the imposition of a formal criminal sanction in combination with increased supervision, although with ambiguous results (Sherman, 2012, Belenko et al., 1994).

We believe, it is the existence of prospective sanctions that mediates the impact of celerity in the context of criminal justice in England and Wales. If an individual has been arrested and is waiting for the court conviction and sentencing while in the community on bail, it might mean that they can be more closely monitored and the sanction for the previous offence has yet to be determined. The government explains bail as follows: "You can be released on bail at the police station after you've been charged. This means you will be able to go home until your court hearing. If you are given bail, you might have to agree to conditions like:

- living at a particular address
- not contacting certain people
- giving your passport to the police so you can't leave the UK
- reporting to a police station at agreed times, e.g. once a week

Failure to comply with these conditions leads to another arrest and remand in custody before the court hearing."[1]

This suggests that monitoring is indeed stricter once someone is out on a bail and longer waiting times would increase crimes rates only for the crimes where detection and probability of getting caught is low. If there are no bail restrictions and probability of being caught again is low (detection rates across crime types can vary by a lot), offender waiting for the punishment can anticipate that they will be able to commit less crime after the sentence is announced and they might commit more crimes whilst waiting. At the same

[1] Taken from https://www.gov.uk/charged-crime/bail

time, one can argue that probability of getting caught *p* would increase while one is waiting for the punishment to be announced via various monitoring methods such as restricted hours when the offender must be at home or reporting to police officers. Therefore, one could argue that celerity effect on crime rates is not that straightforward and can have different effects after you condition on the detection rates. Tittle (1969) found support for the deterrence theory and concluded that the certainty of imprisonment deters crime, however, the severity can only deter crime when certainty of the punishment is reasonably high. In this paper we want to test if the same hypothesis would hold for the celerity as well.

The proposed hypothesis we are trying to answer in this paper would be as follows:

Waiting for justice can have an ambiguous result on crime rates and it would depend not only on future discounting of the criminals but also how the accused during waiting time is being monitored by the police which in turn would affect probability of detection for any crimes committed while waiting. In other words, more serious crimes such as violent crimes, which have higher detection rate, could have a negative effect on crime rates when waiting time is increased and economic crime such as theft, which have a lower detection rate and lowered monitoring, could have a positive effect on crime rates when waiting time is increased.

The existing literature tries to establish different relationships between crime and crime determinants including the impact of various socio-economic variables. Although there is a massive literature on this in the U.S. there has also been a growing number of European and UK studies on crime determinants (see Reilly and Witt (1992), Pyle and Deadman (1994), Witt et al. (1998), Machin and Meghir (2004), Carmichael and Ward (2001), Edmark (2003), Han et al. (2013)). These studies have tested and shown that policing, i.e. detection and conviction rates, as well as socio-economic variables such as higher presence of young people in the community, income and income inequality, unemployment and population density can affect crimes in different ways. This paper contributes to existing literature by exploring crime determinants while including all three variables from classic crime deterrence theory – Certainty, Severity and Celerity. Also, it used three crime types – theft, burglary and violence against the person to check how waiting times, or Celerity, might be affecting them differently through possible increase in detection while waiting for justice.

In this paper we use a data from 41 Police Forces[2] from England and Wales from 1994 to 2008 to test the deterrence theory on the *3 Cs* – Severity, Certainty and Celerity and how they affect different crime rates. We also include a set of control variables such as proportion of young people, population density and lower quartile earnings. We use a fixed effects model to eliminate the unobserved characteristics at police area levels from the

[2] There are 43 Police Forces in England and Wales, however, the data on Celerity (Waiting times measured in number of days) for City of London is not separated into City and Metropolitan Police District, hence, we had to exclude London City and Metropolitan Police.

estimated coefficients. Moreover, we include a dummy for the year 1997 and beyond due to a change in crime counting in England and Wales. To overcome a potential endogeneity of police detection (as one could argue that whilst detection rate can affect crime rate, at the same time crime rates can affect detection rates – if crime rates increases, then less resources would be spent per crime investigation which could lead to lower detection rates as a result which would mean that police detection could be inversely correlated with crime), we use an Instrumental Variable approach. We instrument detection rate with lagged detection and various lags of police expenditure which is not correlated with crime rates – funding to police forces is not dependent on crime rate in the force area, hence, we find it to be a suitable instrument for detection rate[3]. To ensure that our chosen instruments are suitable, we test for the validity and the strength and conclude that the chosen instruments are indeed valid and not weak for all cases.

2.5 Data Description

To conduct our analysis, we use data from 41 Police Force Areas (PFAs) in England and Wales covering the period 1994-2008. The dependent variables in this paper are crime rates for burglary, theft and violence against the person which are expressed as number of offences per 1000 people in each PFA yearly. The first two offence types are categorised as property or economic

[3] Machin and Meghir (2004) also use police expenditure as an instrument for detection

crime type while the last one is a non-economic crime type. The crime rate data are available from Criminal Statistics and Crime in England and Wales published by Home Office. Table 1 reports descriptive statistics for all crime types averaged over the 1994-2008 period.

Table 1: Descriptive statistics of dependent variable	Mean	Standard Deviation
Burglary rate	15.62	7.73
Theft rate	37.18	11.17
Violence Against the Person	11.24	6.12
All crime types are defined as the number of offences per 1000 population There is total of 574 PFA – year observations (41 PFA by 14 years) in the sample		

For explanatory variables, we use detection rate to represent the certainty of the punishment. The lower the detection rate is, the lower the certainty of the punishment would be. Detection rate is measured by the proportion of total recorded criminal offences which had been detected. Detection rates are available for all three crime types we are analysing and are obtained from the Home Office Publication series Criminal Statistics and Crime in England and Wales. Data on detection rates are available yearly at the PFA level. We would expect a negative sign between detection rates and crime rates. If detection rates increase, expected gain from the criminal activity decreases as probability of getting caught p goes up.

We use average sentence to reflect the severity of the punishment which is measured by the average time (given in months) offenders were sentenced to custody. This does not necessarily show the real time spent in the prison but it reflects the Severity of the punishment in our analysis. As with detection, average sentence data are available on all crime types and is available yearly at the PFA level. Data were received from the Ministry of Justice following a *Freedom of Information* request. Many would expect that longer prison sentence should negatively affect the crime rates. Firstly, harsher potential sentence might discourage criminals from committing an offence. Secondly, if criminals are held in prison for longer they have less time to commit crimes outside the prison. However, spending longer time in prison away from family and employment can affect future personal and financial circumstances in a negative way. People facing lower employment opportunities after prison might turn back to criminal activities due to economic reasons. Prisons may also lead to interaction with criminals and access to networks, increasing future crime opportunities. Therefore, we can expect the relationship between sentencing and crime rates to be either positive or negative.

We use the number of days on average an offender had to wait from offence to completion stage of proceeding as our variable representing the swiftness of the justice system. We call it the waiting times variable. It is available yearly at the PFA level and was also obtained from the Ministry of Justice through a Freedom of Information request detailing how many days on average offenders had to wait from offence to completion stage of proceeding. Theory suggests that shorter waiting times should be associated with a lower crime rate as the swiftness of the justice system is a positive crime deterrent. However, we argue that the effect can be ambiguous and some type of offences can result with a stricter bail conditions and/or some offenders might not want to risk being caught again while waiting for the completion stage of proceeding in fear that the sentence given to them then would be harsher.

We include a number of socio-economic variables as controls which are widely used in other crime studies:

Youth is defined as the proportion of people aged 15 to 24 of the whole population in each PFA. Data are available from the Office for National Statistics at the local authority level and had been aggregated to PFAs according to each PFA's geographic boundaries. It was obtained by aggregating two age groups of people aged 15 to 19 and 20 to 24. The reason we include proportion of youth in the population is due to the wide belief that young people commit more crimes. *Youth Justice Statistics* by the Ministry of Justice reports that in 2012 – 2013 there were 1.07 million arrests for notifiable offences in England and Wales, of which 126,809 were of people aged 10 – 18 years. That accounted for 11.8 per cent of all the arrests while all 10-17 year olds account for 10.5 per cent of the total population of those ages 10 or above (people of offending age) in England and Wales. Young adults aged 18 to 25 make up 10% of total population, however they account for a third of those sent to prison each year (Prison Reform Tryst, 2012). This could be explained by the lower opportunity cost of committing crime for young offenders. First of all, young people tend to have lower earnings, therefore, if they were caught, they would lose less financially than someone older with higher wages. Second of all, juvenile offenders tend to get more lenient punishments for committed offences. For those reasons, a higher proportion of young people in the population could be associated with higher crime rates. However, young people could also be deterred from committing crimes due to possible negative outcomes on their future labour market opportunities. Therefore, we can expect either a negative or a positive sign between crime rates and youth population in the PFA.

We use lower quartile earnings coefficient to account for income inequality across England and Wales as this data are available yearly at the PFA level from the Annual Survey of Hours and Earnings. It can be argued that the increase in the lower quartile earnings could affect crime rates negatively due to less economic incentive to commit a crime with increases in income (Machin and Meghir, 2004).

Population density is measured as population per square kilometre. Data are available from Criminal Statistics and Crime in England and Wales published by the Home Office. It is available yearly at the PFA level. The effect of the population density on crime could be ambiguous – more densely populated areas could have higher crime rates due to more opportunities for crime to take place (more people, more vehicles, more goods to be stolen), however, with more people being around the offender might be easily seen by witnesses and the police are more likely to respond quicker than in a less populated area.

Descriptive statistics for all explanatory variables averaged for 1994 – 2008 period, are reported in Table 2 below.

Table 2: Descriptive statistics of explanatory variables	Mean	Standard Deviation
Detection rate - burglary	17.14	7.39
Detection rate – theft	22.03	6.56
Detection rate – violence against the person	67.94	15.7
Average sentence – burglary	15.66	2.75
Average sentence – theft	4.92	1.3
Average sentence - violence against the person	16.91	2.19
Waiting times – burglary	126.33	30.85
Waiting times – theft	104.4	22.62
Waiting times - violence against the person	119.84	22.57
Youth	12.29	1.12
Q25	1.71	0.18
Population Density	423.95	406.03

2.6 Econometric Specification

We start our methodological analysis by looking at the simple linear crime function where crime rate is determined by *3 Cs* – Detection which is used for the Certainty, Average Sentence which is reflects Severity and Waiting Times which are used for the Celerity and various socio-economic variables. Our proposed empirical model is

$$Crime_{i,t} = \beta_1 Certainty_{i,t-1} + \beta_2 Severity_{i,t-1} + \beta_3 Celerity_{i,t-1,t} + \beta_4 Youth_{i,t} + \beta_5 Q25Earnings_{i,t} + \beta_6 PopulationDensity_{i,t} + Dummy + \sigma_i + \varepsilon_{i,t} \tag{1}$$

where i represents the Police Force Authority, t represents time, σ_i is the unknown intercept for each PFA, and $\varepsilon_{i,t}$ is the error term. *Crime* stands for the crime rate per 1000 people, *Certainty* stands for the detection rate, *Severity* stands for the average sentence issued in months, *Celerity* stands for the average waiting time from the offence to completion stage of proceeding in days[4], *Youth* stands for the proportion of young population aged 15 to 24, *Q25Earnings* stands for the lower quartile earnings coefficient and *PopulationDensity* stands for the Population Density in each PFA. We also include a dummy variable since there was a change in counting rule in 1998 April. Prior the change, crime was counted from 1 January till 31 December and after the change it was started to count from 1 April to 31 March next year making it coincide with the financial year. Also, some definitions of crime types have been broadened which led to upward shifts in crime rates since 1998. The dummy variable has a value of one for the post change periods and zero otherwise. Also, since there is an overall positive trend for violence

[4] In Appendix A.2 we also report Tables 30 and 31 where we estimate the same model and report the results when we drop (i) Celerity and (ii) Severity.

against the person rate and overall negative trend for theft and burglary rates (Appendix A.1) we include a time trend in our model. All variables (apart from time trend and dummy) are in natural logarithms to make interpretation easier in elasticity form. Also, for detection, average sentence and waiting times variables we use lagged values. There are two reasons why we believe they have to be lagged: theoretically, the offender's perception of risk and punishment (whether it is how likely they are to be caught, how swiftly they would be sentenced and how long they would spend in prison) will not instantly adapt to reality but more gradually and, practically, there is some time delay from when convictions happen and when the crime was committed. Additionally, using lags reduce the problem with the potential reverse causality of each of these variables which depend on the number of recorded crimes as we explain in more detail below.

We start by estimating a fixed effects model which eliminates unobserved area specific time invariant effects and then we employ an Instrumental Variable approach (IV) fixed effects model to overcome potential issue with endogeneity of detection rate. If crime rate and detection rate are endogenous we would get inconsistent results with our estimation since detection rate would be associated not only with changes in crime rate but also with changes in the error term. Therefore, finding a suitable instrument which would be correlated with detection but not directly affect crime rate, can help us overcome potentially inconsistent estimates. It could be argued that whilst detection rate can affect crime rate, at the same time crime rates can influence detection rates – if crime rates go up, then fewer resources would be spent per crime investigation which in turn can lead to lower detection rates as a result. In that case we would be capturing a spurious relationship between detection and crime rates. Therefore, we use an IV approach where the first lag of detection is being instrumented with other variables which are correlated with detection itself but are not correlated with crime rates. To instrument the first lag of detection we use second lag of detection for all crime types plus lagged police expenditure[5]. We believe that police expenditure is a suitable instrument because it is determined by a Police Allocation Formula which is not directly determined by crime rates reported in each PFA but is based on various socio-economic variables that helps to predict the workload for the forces. In order to test for instruments validity and strength, we perform appropriate tests. Firstly, to test for the validity we check if instrument passes Sargan's and Basmann's tests, secondly, to check whether instruments are weak we calculate the minimum eigenvalue statistic by Cragg and Donald and check it against Stock and Yogo weak instrument test critical values. All instruments passed both tests, therefore, we can be sure that our chosen instruments are valid and are not weak.

One could similarly argue that when crime rates go up, sentencing and waiting times would be affected which would cause issues of potential endogeneity. As for sentencing, sentencing guidelines which are set by the Sentencing

[5] For violence against the person we use the first lag of real police expenditure, for theft and burglary we use the third lag of real expenditure per police officer

Council for England and Wales help to ensure that all courts are consistent in their approach to sentencing. They provide guidance on factors that the court should take into account when deciding on a sentence which is the same across England and Wales. Therefore, we believe there should be no major issue with endogeneity for sentencing variable and as noted above we are using a lagged value for sentencing variable. Waiting times could be affected by the volume of crime reported as courts would have to deal with a larger number of hearings and that could in turn cause delays in how swiftly the crimes are resolved. However, there is a vast variation in average investigation and hearing times between different offences and importantly for guilty plea and not guilty plea trials. Furthermore, the biggest single reason accountable for a trial being recorded as ineffective (which means a delay and rescheduling for a future date when a trial could not take a place on a scheduled day) has been identified as court administration suggesting that waiting times are not only affected by crime numbers but also by how they are administered as a number of participants would then not attend a court and the absence of witnesses and defendants would prolong the process and increase waiting times (Rossetti, 2015). Also, as noted earlier we are using the first lag of waiting times variable to further reduce endogeneity.

2.7 Results

The empirical results are provided in the tables below. Table 3 gives results from the fixed effect model and Table 4 gives results using the Instrumental Variable Approach.

Table 3: Fixed Effects Regression Models			
Fixed Effects			
	Theft	Burglary	VATP
Certainty (t-1)	**-0.29***** (0.03)	**-0.17***** (0.04)	**-0.28***** (0.09)
Severity (t-1)	**-0.08***** (0.03)	**-0.2**** (0.08)	**0.28**** (0.11)
Celerity (t-1)	0.02 (0.03)	0.05 (0.04)	**-0.24***** (0.06)
Youth	-0.00009 (0.2)	-0.42 (0.39)	-0.14 (0.64)
Population Density	-0.43 (0.38)	-1.1 (0.57)	0.44 (0.78)
Lower Quartile Earnings Ratio	0.06 (0.17)	0.79 (0.51)	0.41 (0.35)
Time trend	Yes	Yes	Yes
Dummy	Yes	Yes	Yes
N	568	337	538
R^2 (within)	0.7	0.85	0.85
Note: dependant variable is the crime rate per 1000 people, robust standard errors are clustered at the PFA level. Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively. All variables in natural logarithm apart from the time trend.			

For the fixed effects model, the lagged detection rate is statistically significant at 1% level for all crime types. As expected it has a negative effect on crime rates, suggesting that when detection rates go up crime rates go down. A 1% increase in detection rate would lead to 0.29% decrease in theft, 0.17% decrease in burglary and 0.28 % reduction in violence against the person rates. Lagged sentencing coefficients are significant for theft and burglary (which combined accounts for more than half of total crimes between 1994 to 2008 in England and Wales) and a 1% increase would reduce theft and burglary by 0.08% and 0.2% respectively, also, for violence against the person has a significant and positive coefficient suggesting that a 1% increase in sentencing would increase violence against the person by 0.28%. Lagged waiting time coefficients are insignificant for burglary and theft rates, however, it is significant and negative for violence against the person. A 1% increase in waiting days would decrease violence against the person rate by 0.24%. This finding supports our hypothesis that longer waiting times for justice system to decide on a suitable punishment to offenders can have an ambiguous effect on crime rates. In particular, violent crimes can take longer to be resolved through the criminal justice system, whilst imposing a stricter bail conditions on the offenders while they are waiting. All socio-economic variables apart from population density on burglary are insignificant.

Table 4: Instrumental Variable Approach			
Instrumental Variable Approach			
	Theft	Burglary	VATP
Certainty (t-1)	**-0.43*** (0.04)	**-0.33*** (0.06)	0.04 (0.19)
Severity (t-1)	-0.05 (0.03)	**-0.17** (0.08)	**0.36*** (0.08)
Celerity (t-1)	0.02 (0.02)	0.05 (0.04)	**-0.24*** (0.06)
Youth	-0.18 (0.18)	-0.14 (0.33)	-0.07 (0.5)

Population Density	0.006 (0.22)	**-1.12**** (0.45)	0.53 (0.59)
Lower Quartile Earnings Ratio	0.01 (0.14)	0.09 (0.37)	**0.66*** (0.4)
Time trend	Yes	Yes	Yes
Dummy	Yes	Yes	Yes
N	523	303	500
R^2 (within)	0.67	0.83	0.81
Note: dependant variable is the crime rate per 1000 people, robust standard errors are clustered at the PFA level. Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively. All variables in natural logarithm apart from the time trend.			

The Instrumental Variable approach results are similar to the ones reported with the fixed effect model. Lagged detection rate is still statistically significant at 1% level for theft and burglary offences, however, it drops significance for violence against the person crime category. A 1% increase in lagged detection rate would reduce theft rate by 0.43% and burglary rate by 0.33%. Lagged sentencing remains statistically significant for burglary and violence against the person offences but drops significance for theft. A 1% increase in lagged sentencing would decrease theft by 0.05%, burglary rate by 0.17% and increase violence against the person rate by 0.34%. The effects of waiting times remain the same and there is no significant effect on either economic crimes but the significant and negative relationship remains between waiting times and violence against the person. The size of the coefficients does not change either and a 1% increase in waiting times would reduce violence against the person rate by 0.24%. For socioeconomic variables population density has a significant and negative coefficient for burglary rates at 5% significance level and lower quartile earnings ratio gets a significant and positive coefficient for violence against the person rates at 10% significance level. Thus, our findings using Instrumental Variable approach remain close to the ones in the fixed effects model. Also, the effect of the waiting days for the punishment to be announced remains exactly the same for the violence against the person offences. Longer waiting times, in fact, might reduce crime rates. Whilst the impact on celerity alone may encourage offenders to commit more crime the longer they wait, there is also an effect of possible monitoring imposed while they wait which would act in the opposite direction. Therefore, we can argue that the net effect we see on the violence against the person crime category is because the monitoring variable is stronger. Our results show that classic deterrence theory which claims that in order to fight and deter crime you need a certain, reasonably severe and swift punishment might not necessarily be fully supported by empirical findings. While certainty (detection) is unarguably a significant variable in crime deterrence, severe punishment and swiftness in justice system might not act as a significant crime determinant or at least not for all crime categories.

2.8 Quadratic model

We are also interested in checking whether longer waiting times for the punishment to be decided and announced can have a potential turning point – the point where the effect of longer waiting times changes from negative to positive in terms of decreasing crime to increasing crime if offender is waiting for longer or the opposite. In order to test for this, we test a model where alongside lagged waiting times we also include a quadratic term of the lagged waiting times:

$$Crime_{i,t} = \beta_1 Certainty_{i,t-1} + \beta_2 Severity_{i,t-1} + \beta_3 Celerity_{i,t-1,t} + \beta_4 Youth_{i,t} + \beta_5 Celerity^2{}_{i,t-1} + \beta_6 Q25Earnings_{i,t} + \beta_7 PopulationDensity_{i,t} + Dummy + \sigma_i + \varepsilon_{i,t} \tag{2}$$

where *i* represents PFA, *t* represents time, σ_i is the unknown intercept for each PFA, and $\varepsilon_{i,t}$ is the error term. The rest of the variables are the same as in the main specification above. *Celerity²* stands for the quadratic form of the waiting times variable.

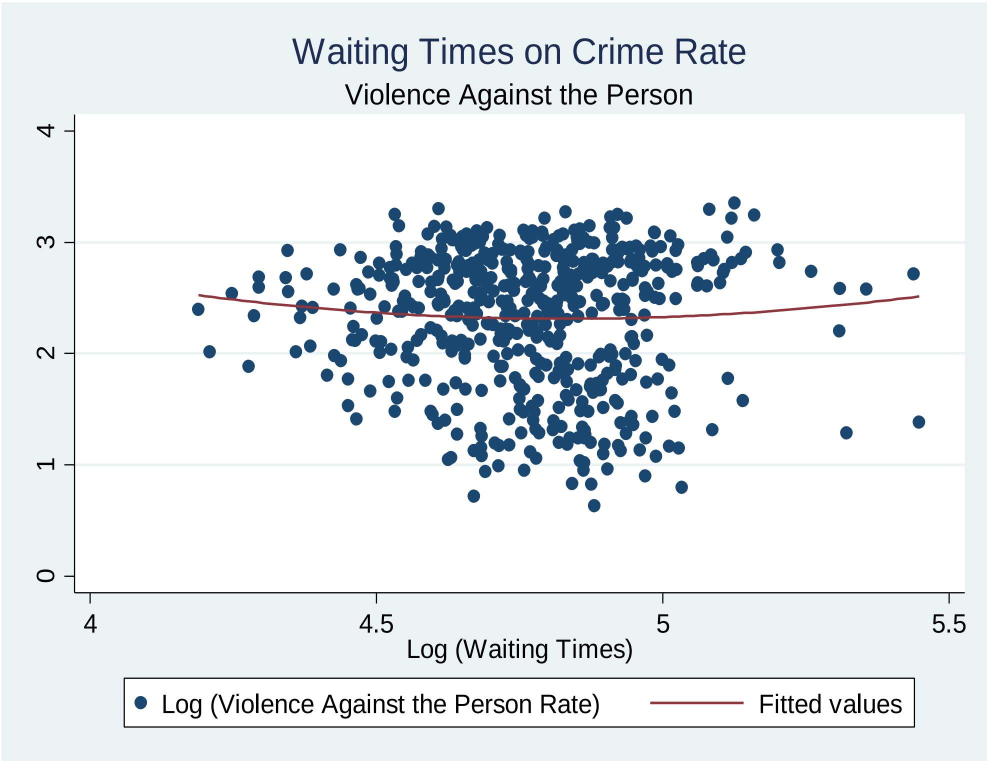
Results for quadratic model is presented in the Table 5 below.

Table 5: Fixed Effects – quadratic model			
	Theft	Burglary	VATP
Certainty (t-1)	**-0.29*** (0.03)	**-0.17*** (0.04)	**-0.28*** (0.08)
Severity (t-1)	**-0.08*** (0.03)	**0.20*** (0.08)	**0.29**** (0.11)
Celerity (t-1)	0.16 (0.53)	0.32 (0.9)	**-3.9**** (1.7)
Celerity (t-1) squared	-0.02 (0.06)	-0.03 (0.1)	**0.38**** (0.38)
Youth	-0.0001 (0.21)	-0.41 (0.4)	-0.1 (0.68)

Population Density	-0.42 (0.36)	**-1.12*** (0.56)	0.43 (0.76)
Lower Quartile Earnings Ratio	0.06 (0.17)	0.79 (0.5)	0.48 (0.76)
Time trend	Yes	Yes	Yes
Dummy	Yes	Yes	Yes
N	568	337	538
R^2 (within)	0.7	0.85	0.85
Note: dependent variable is the crime rate per 1000 people, robust standard errors are clustered at the PFA level. Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively. All variables in natural logarithm apart from the time trend.			

Results remain consistent with the ones discussed in the result section. Squared waiting time variable is only significant for the violence against the person crime category. It is positive and significant while linear term is negative and significant which suggests a non-monotonic relationship between waiting times and crime rate for violence against the person. Figure 1 below illustrates a plotted regression line with the scatter plot and illustrates the relationship between violence against the person rate and waiting times.

Figure 1: Waiting Times on Crime Rate



In order to calculate the turning point, we need to take derivatives and calculate from what waiting time length crime rate starts to increase (full calculations can be found in the Appendix A.2). We find that violence against the person crime rate decreases while the waiting time in days is 164 or less, however, after that point, if waiting times are prolonged crime rate starts to increase. From our data we know that average waiting time for violence against the person is 120 days, hence, on average the effect of the current average waiting time in days is crime reducing. However, it is important to note, that if waiting times increase significantly, it will not in turn reduce the overall violence against the person crime rates but may in fact increase it.

2.9 Conclusion

There is a lot of debate about crime prevention and the effectiveness of the justice system, however, not all of it is based on formal quantitative analysis. We try to contribute with this study by providing an econometric analysis to enrich the understanding of how the effectiveness of the justice system actually affects different crime rates. In line with previous research, we find that detection plays a consistent role in reducing crime, and that severity of sanctions is ambiguous. For celerity, we find no significant effect for most crime types. However, for violence against the person, we find the opposite of what classical deterrence would predict. For that crime type, a longer period from crime committed to court sanction is associated with lower re-offending. This goes against the predictions of classical deterrence theory that would suggest some degree of substitution between different aspects of the sanction. If an individual has been arrested and is waiting for the court conviction and sentencing while in the community on bail, it might mean that they can be more closely monitored and the sanction for the previous offence has yet to be determined. Therefore, our celerity variable might be capturing both the celerity and monitoring variable which acts in opposite directions and, hence, the effect on violence against the person shows that the monitoring variable has a stronger effect between the two. One of Becker's predictions is that increased severity should have the same impact as increased certainty, implying that costly enforcement of the law could be reduced in favour of higher penalties. One response to this not being empirically borne out is to suggest that these elements of deterrence cannot be conceptually separated from each other and that their impacts need to be considered as one package (Mendes, 2004, Mendes and McDonald, 2001, Howe and Brandau, 1988). Our suggestion is that some of these differences reflect the variable impact of specific and general deterrence, and in particular, the difference between the experience of punishment and the future prospect of it.

3. Alternatives to custody: evidence from police force areas in the United Kingdom[6]

3.1 Introduction

World-wide prison populations have increased substantially since the mid-1990s In England and Wales, the prison population increased from around 17,400 in 1900 to over 85,300 in 2016, and in March 2017 the total prison population was just over 85,500 (Allen et al., 2017). In 1901 there were 86 prisoners per 100,000 head of population which increased to 182 per 100,000 head of population by 2016. Incarceration is an expensive and socially divisive response to crime but its use is often justified not only on grounds that it is a fitting punishment but also in the belief that it reduces crime. Its effectiveness is contested (Jolliffe and Hedderman, 2015) and given its costs, finding effective alternatives to custody is a key motivation for policymakers and question for researchers. This question has become even more urgent following the financial crisis and the demand for governments to make cuts in public services, including the criminal justice system (Neilson, 2010, Bandyopadhyay, 2013). While community sentences have existed in some form since 1907 (Solomon and Silvestri, 2008), in recent decades criminal justice legislation has expanded the range of formal requirements available to courts when imposing them. These can include regular supervision, electronic tagging, curfews, unpaid work and participation in drug rehabilitation

[6] The analysis in this chapter is partly based on Abramovaite et. al 2018

programs. Similar requirements can be imposed as orders that are part of a suspended prison sentence. As a result, courts in England and Wales now have the power to sentence offenders to a range of non-custodial alternatives with varying levels of prospective deterrence, punishment severity, surveillance and associated rehabilitative support. This paper offers an empirical analysis of how effective these alternative sentences are at reducing crime compared to custody.

The annual average cost for each prison place is £36,808 (figure for England and Wales, 2012-13, taken from Prison Reform Trust, 2014)[7] while each new prison place is estimated to cost £119,000. By contrast, an intensive community order costs between £10,000 and £15,000. A Home Detention Curfew for 90 days is estimated to cost £1,300 compared to £6,500 for a similar period in custody (Heard, 2015). Although much cheaper, the effectiveness of these alternatives to custody at achieving crime reduction has not been fully explored.

The impact of incarceration on crime reduction is theoretically ambiguous since there are many counter-balancing effects through which prison can affect crime rates (Friehe and Miceli, 2017). The key mechanisms through which prison is theorised to reduce crime is: incapacitation of individual

[7]http://www.prisonreformtrust.org.uk/Portals/0/Documents/Prison%20the%20facts%20May%202014.pdf

offenders, which prevents crime against the community while they are incarcerated; specific deterrence in which prison, as punishment, dissuades an offender from committing crime in the future; and general deterrence which is supposed to discourage a population of potential offenders from committing crime through the prospect and expectation of punishment (Becker, 1968, Kessler and Levitt, 1999).

However, there are also mechanisms through which prison is theorised to have criminogenic effects (Engelen et al., 2016). Prisons can: prevent offenders from acquiring useful skills in legitimate labour markets, label offenders formally as deviant, marking them as unsuitable for reintegration into society, have psychologically destructive effects that prevents prisoners from returning to normal life when released, reduce access to and even destroy familial relationships and other sources of social support and integration; and generate a pro-crime environment where prisoner peer groups, and even prison officers, reinforce deviant identities and behaviours (Smith et al., 2002, Cid, 2009, Cullen et al., 2011). At the most extreme end of the criminogenic spectrum, incarceration can foster prison gang membership with significantly increased recidivism on release (Dooley et al., 2014, Skarbek, 2011).

As Durlauf and Nagin (2010) summarise, prison is not just a punishment. It is also a concentrated experience of socialisation with other offenders. Former prisoners can struggle to find legitimate work but may have developed lasting associations with other criminals, making crime more materially attractive and normatively acceptable. In the United Kingdom, sceptics of penal sanctions point to frequently high re-offending rates on release from prison as evidence of some of these effects (Hedderman, 2008).

Our contribution is to use a unique panel data at Police Force Area level in England and Wales in order to understand the impact of alternative sentencing policies such as community sentences on crime rates. This data set was requested through a *Freedom of Information* request. It details how many different sentences have been issued for all crime types each year from 2002 to 2013. This data set allows us to distinguish between the number of prison sentences (custody) and non-custodial sentences (community sentences, conditional discharge, fines and suspended sentences) imposed by local courts. We exploit the significant sentencing discretion traditionally granted to local courts (Brownlee and Joanes, 1993, Tombs and Jagger, 2006, Pina-Sánchez and Linacre, 2013, Pina- Sánchez et al., 2017), and plausibly maintained even after the introduction of compulsory sentencing guidelines (Roberts, 2011). This allows for a more detailed examination of criminal justice practice on PFA level crime than has yet been achieved in the United Kingdom, and is rarely matched elsewhere in the world. We analyse the effect of alternative sentencing methods on crime rates in the PFAs by using sentence type and offence type conviction rates derived from data on total number of sentences across all PFAs each year. Our data are offence-type specific. Therefore, it allows us to explore alternative sentencing effects on different crime types. Our model of using variations in sentencing data across PFAs, rather than prison population, means that we can compare the different ways in which courts use prison as a sentencing option, rather than just how much they are using them, and avoid some of the well-established problems with using prison data (Spelman, 2008).

We show that prison, in some circumstances, can be effective at reducing acquisitive crime, but that alternatives to custody are also effective in many cases. Although our results are most directly applicable to England and Wales, they have relevance to a more general understanding of criminal justice effectiveness. Our data cover a range of sentencing practice which, although still punitive by European standards, involves markedly less overall incarceration than in the United States (Tonry, 1999). Our study might help to provide some tentative support for arguments that sentencing policy can be reformed to rely less on punitive sanctions to reduce crime.

An important caveat is that it is not possible to disaggregate all the mechanisms through which criminal justice might affect crime rates. As Durlauf and Nagin (2010) note of panel data approaches generally, 'these studies are actually measuring a combination of deterrent and incapacitation effects'.

3.2 Previous research

3.2.1 The effects of sentencing policy on individual offenders

An array of randomised controlled trials (RCTs) have examined the effects of short periods of custody on offenders compared to alternative sentences (Killias et al., 2000, Killias and Villetaz, 2008, Killias et al., 2010). The results are not conclusive but suggest that prison for low-level offenders might have a small criminogenic effect, but that existing offender characteristics are much larger predictors of criminal career prospects. These studies (Killias et al. 2000, Killias et al. 2010) followed 123 subjects randomly assigned to community sentence or immediate short term custody in Switzerland. After two years, the results showed no difference with respect to subsequent employment history, and social and private life circumstances, but re-arrest by the police was more frequent among those randomly assigned to prison than among those selected for community service. However, eleven years later, ex-prisoners had more positive outcomes. They complied more consistently with tax regulations, and fared no worse regarding employment history or marital status. In line with recent systematic reviews, the results do not suggest that short custodial sanctions are harmful when compared to community service. However, the evidence is still relatively limited.

Although RCTs have arguably the highest levels of internal validity, how far these results can be extrapolated to a general population of offenders is questionable. It is rare that justice systems can permit random selection of sanctions. When they do, the offenders studied are necessarily low-level, as they have to be eligible for a community disposal. Comparatively small numbers of offenders are included in these studies with the result that small effects might be hard to detect with certainty.

Matching studies, therefore, allow for a much wider comparison of offenders. Smith et al. (2002) systematically reviewed studies which compared the effects of community sentences with custodial sentences. They restricted their survey to those with good study designs which controlled for offender characteristics and found 31 eligible studies. A small effect suggesting that prison sentences might be associated with increased recidivism was found. They concluded that variations in the kind of sentence 'did not produce decreases in recidivism' although they did find 'tentative indications that increasing lengths of incarceration were associated with slightly greater increases in recidivism'.

Cid (2009) examined the effects of custodial versus non-custodial sentences on recidivism. They conducted an eight year follow up study where rates of reoffending between former prisoners and offenders who served a suspended prison sentence were compared. This study concluded that the offenders given suspended sentences had a lower risk of reoffending than those given prison sentences. Jolliffe and Hedderman (2015) analysed the effect of prison and community sentence on future offending. They used a sample of 5,500 offenders from 1 of 10 regions in the United Kingdom. Using propensity score matching to balance pre-existing differences between two groups of offenders, they found that incarcerated offenders tended to commit more offenses after their release and started reoffending earlier than those supervised in the community. They concluded that alongside other emerging evidence prison sentences tends to slightly increase the chances of future offending.

Nieuwbeerta et al. (2009) identified the effects of first-time incarceration on individual offenders in the Netherlands. They used risk-matching to control for individual differences between offenders given custodial sentences compared with alternatives. They examined criminal activity 3 years following the different judicial interventions, and concluded that being incarcerated had a criminogenic effect, putting offenders on a more serious criminal career path. Similarly, Wermink et al. (2010) found that offenders reoffended significantly less after completing community sentence compared to a short term imprisonment.

Andersen (2015) analysed full-sample individual-level data in Denmark, using difference-in-differences matching to measure the effects of doing community sentence as an alternative to serving a prison sentence. This study had the benefit of measuring several short and long-term post-sentence outcomes. The results suggested that offenders given a community sentence had higher incomes and were less dependent on social benefits in the long term. However, there was no overall evidence of lower recidivism rates.

Andersen and Andersen (2014) found that electronic tagging, as an alternative to prison, had a similarly beneficial impact on juvenile offenders.

The Ministry of Justice in the United Kingdom performed its own study, comparing incarcerated offenders with those given community sentences, matching them by propensity to be imprisoned (Bell, 2011). The results suggested that those given community sentences were less likely to re-offend. However, the same approach, comparing matched offenders given different lengths of prison sentences found that offenders imprisoned for longer tended to be less likely to re-offend. One potential weakness in this study is that it compared prisoners on release to other offenders just starting a community sentence, thus excluding the incapacitation element of the prison sentence while including the potential incapacitation associated with a community sentence.

Marsh and Fox (2008) used the estimates of the differential impact of sentencing into estimates of the economic efficiency of alternative sentencing options in the UK. They concluded that standard prison sentences are not an economically efficient means for reducing re-offending. They found that diverting adult offenders from standard prison sentences to alternative interventions saves the UK public sector between £19,000 to £88,000 per offender. Also, when considering victim costs, diverting offenders from standard prison sentences saves between £17,500 to £203,000 per offender.

Marsh et al. (2009) reviewed 19 studies and identified 91 estimates of the effect on re-offending of prison for adults when compared against alternative sentences and 15 estimates of the effect on re-offending of prisons for juveniles when compared against alternative sentences. After conducting a meta-analysis on the different combinations of interventions, they suggest that the following alternative sentences for adult offenders reduce re-offending when compared to prison: residential drug treatment, surveillance, surveillance with drug treatment, prison in combination with educational/vocational interventions, prison in combination with behavioural interventions, prison in combination with sex offender treatment, and prison in combination with drug treatment. In addition, two types of alternative sentences for juvenile offenders - community supervision with victim reparation, and a community programme with aftercare and surveillance – reduced re-offending when compared to prison. They concluded that prison sentences are generally not an efficient means of reducing re-offending in the UK, however, they also highlighted that despite their efforts to focus on the best research designs available some studies failed to eliminate differences between the treatment and control groups , used poor research design, much of the data available were collected in the USA and there were large amounts of variability in the effect sizes particularly for the enhancements to prison for adult offenders such as education/vocational interventions, sex offender treatments and drug treatment in prison.

3.2.2 The effects of sentencing policy on aggregate level data

Not all of the theorised effects of sentencing involve only the effect on individual offenders. The use of district-level data are important additions to our understanding of how the criminal justice system influences a community's experience of crime. Whereas studies of re-offending statistics can only capture the effect of criminal justice interventions on subsequent re-offending by individuals, panel data, in principle, can estimate the number of crimes prevented through incapacitation and general deterrence in a population of potential offenders.

In the United States, several panel studies have been used to explore the effects of incarceration on crime rates (Durlauf and Nagin, 2010). The results were inconsistent, with only some studies suggesting that prison population growth had a small deterrent effect. Vieratis et al. (2007) combined panel data of prison growth and prisoner releases. They found that prison growth was associated with lower crime but that releasing prisoners was associated with higher crime and because they controlled for changes in prison population levels they attributed this effect to the criminogenic effects of incarceration. This suggests that the crime reduction effect of more incarceration can be short-lived, and that use of prison might be a double-edged sword that can easily prove counter-productive. More recently, Spelman (2013) offered a solution to disentangling the co-dependence of crime and prisons, by finding instruments for crime that predict changes in prison population, before deriving the effects of prison on crime. His results suggested that increased use of prison was, on balance, crime reductive in the US.

In Europe, a panel study comparing justice systems in German states (Spengler, 2006) found that higher conviction rates were associated with lower crime rates but not the form, or severity, of sanction. Another panel of Greek regions (Saridakis and Spengler, 2012) found that property crime was deterred by higher clear-up rates and reduced by lower unemployment, but these effects were generally insignificant for violent crime.

In the United Kingdom, a number of researchers have used police force areas (PFAs) and counties to develop panel level data and explore crime rate relationship with other factors. Witt et al. (1999) linked increasing wage inequality and more cars per capita with higher crime, but also found that a larger police force was associated with lower property crime. Carmichael and Ward (2001) established a systematic positive relationship between most crime and male unemployment. Machin and Meghir (2004) found that fewer opportunities for low-wage work were associated with higher acquisitive crime, and also suggested that potential offenders are deterred by higher conviction rates. Han et al. (2013) found strong relationships between higher police detection rates and lower crime rates in subsequent years. Bandyopadhyay et. al (2012) explore how variation in sentence length affect crime rates. However, few non-U.S. analyses have been able to explore variation in sentencing subsequent to conviction. An important exception to this is Bell et al. (2014) which exploits variation in sentence severity following the 2011 riots in London to identify a deterrent effect of harsher sentencing. Our approach, therefore, has the unique advantage of observing sentencing variation in hitherto unexamined detail.

3.3 Data

We obtained a unique dataset from the Ministry of Justice through a *Freedom of Information* request detailing how many different sentences have been issued for those crime types in each year. In the UK, sentencing is classified into custodial and non-custodial. Custodial sentences include immediate custodial sentences (both of determinate and indeterminate length) and suspended sentences. Non-custodial sentences include fines, community service, conditional discharge and absolute discharge. Our data include the total number of sentences issued to adult and juvenile offenders in each PFA every year for each sentence type as listed above. We use this data to test whether different sentencing (with a lag) has a different effect on crime rates. As we have data on sentencing for adults and juveniles separately, we analyse the effects of sentencing for both age groups jointly and then separately. Total crime committed by the juvenile offenders is lower than adult offenders. However, young people are over represented in the criminal justice system.[8]

[8] In 2012/13 police made around 1.07 million arrests. 11.8 per cent of those (total of 126,809) were young people aged 10 – 17 and for notifiable offences. In that year, young people accounted for 10.5 percent of the offending age population (10 years old or older) which suggests that young people are over-represented in the criminal justice system.

Therefore, it is useful to analyse the effects of sentencing juvenile offenders on crime rates separately to adult offenders.

Our data show us at each PFA[9] in England and Wales, (from 2002 to 2013) how many crimes have been recorded in four different crime categories – violence against the person, sex offences, robberies and property crimes. These four crime categories account for around 90 per cent of total crimes recorded across England and Wales between 2002 and 2013 (Appendix B.1). The majority of offences were categorised under the property crime category. Graph 2 in the Appendix B.2 shows the composition of property crime. The main categories being criminal damage, all other theft offences, vehicle thefts and burglary offences. For violent crimes, violence against the person accounts for the majority of the total violent offences recorded (Appendix B.3).

Our dependent variable is crime rate per 1000 people for each PFA for each time period. Our analysis includes violence against the person, sex offences, robbery and property crimes. As we are interested in how sentencing works and how alternatives to custody affects crime rate, for our independent variables, we derive "sentence-conviction rate" which we derive by taking the total number of criminals sentenced to, for example, custody in the particular year in each PFA and dividing that number by the total number of crimes

[9] We are using data for all PFAs apart from the City of London because it is a small area that contains the Central Criminal Court of England and Wales (colloquially known as the Old Bailey) which tries cases from outside the area.

registered in each PFA that year and multiplying it by 100 to derive a rate. "Sentence-conviction rate" can be represented as following:

$$"Sentence - conviction\ rate" = \frac{Total\ Number\ Sentenced\ per\ Sentence\ Type_{crime\ type,year}}{Total\ Number of Crimes_{crime\ type,year}} * 100$$

We do this for all crime types listed above. Our derived conviction rate for each sentencing type (and for each offence type) is correlated with detection rate as only the detected crimes get sentences issued to the offenders. Conviction rate is sometimes used as a proxy for detection rate (Machin and Meghir 2004). Moreover, this type of conviction rate allows us to look into each sentencing type separately. While we have sentencing data separated for adult and juvenile offenders and the effect of that can be captured separately, recorded crime rate has a victim but cannot be matched with an offender (in a large percentage of cases we do not even know who the offender is), and thus we cannot separate our dependent variable to crime rate for adult offenders only or for juvenile offenders only. Therefore, we run two empirical models – one with total sentence-conviction rate for all of the offenders and another one where sentence-conviction rate is separated for adult and juvenile offenders. Descriptive statistics for all four crime types averaged for 2002 – 2013 period are reported in Table 6 below.

Table 6: Descriptive Statistics od Dependent Variables	**Mean**	**Std. Dev.**
Violence Against the Person (VATP) – rate per 1000 people	12.18	3.08
Sex Offences – rate per 1000 people	0.96	0.21

Robbery – rate per 1000 people	0.91	0.94
Property crime – rate per 1000 people	58.27	19.24
Note: All crime rates are defined as the number of offences per 1000 population; There is a total of 504 "PFA – year observations" in the sample (42 PFA by 12 years)		

We include data on unemployment and proportion of youth population so that we can control for socio-economic factors which could contribute to changes in crime rates. Also, we include a total of police officers' salaries as that represents the strength of the police presence and might affect crime rates. Unemployment rate is defined as a proportion of unemployment benefits claimants to the total number of people in the workforce. We obtained unemployment figures from Labour Force Survey and Annual Population Survey. Unemployment data are available yearly at each PFA level. Police officers' salaries are the totals (in £'000) of how much each PFA spent yearly on police officers' salaries (CIPFA). The variable youth population is defined as a proportion of young people aged 15 to 24 to the entire population. The data source is mid-year estimated population by age and gender from National Statistics. The number of people aged 15 to 24 has been calculated by aggregating each year group at local authority level and then it was aggregated into PFAs according to their geographic boundaries. Descriptive statistics for conviction rates and socio-economic variables are reported in Table 7 below.

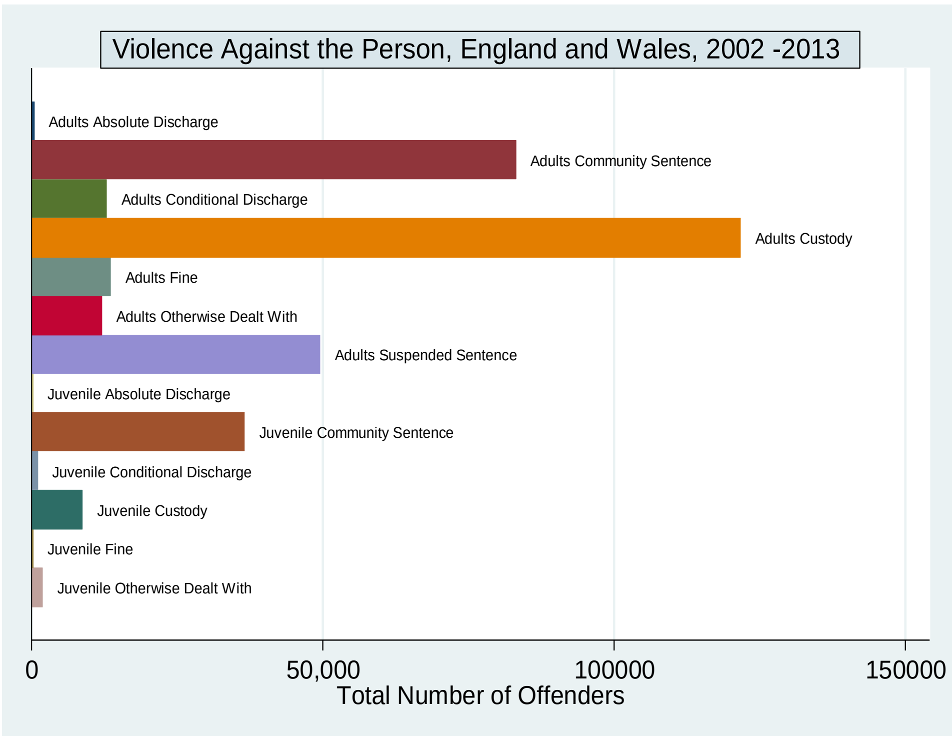
Table 7: Descriptive Statistics of Explanatory Variables	Mean	Std. Dev.
VATP – Conviction Rate for Community Sentence	1.59	0.72
VATP – Conviction Rate for Custody	1.65	0.56
VATP – Conviction Rate for Conditional Discharge	0.19	0.11
VATP – Conviction Rate for Fine	0.2	0.12
VATP – Conviction Rate for Suspended Sentence	0.69	0.54
VATP - Adult Conviction Rate for Community Sentence	1.12	0.53
VATP - Adult Conviction Rate for Custody	1.55	0.53
VATP - Adult Conviction Rate for Conditional Discharge	0.17	0.1
VATP - Adult Conviction Rate for Fine	0.19	0.12
VATP - Adult Conviction Rate for Suspended Sentence	0.69	0.54
VATP - Juvenile Conviction Rate for Community Sentence	0.47	0.24
VATP - Juvenile Conviction Rate for Custody	0.1	0.06
Sex Offences – Conviction Rate for Community Sentence	2.72	1.01
Sex Offences – Conviction Rate for Custody	5.73	1.77
Sex Offences – Conviction Rate for Conditional Discharge	0.27	0.26
Sex Offences – Conviction Rate for Fine	0.28	0.34
Sex Offences – Conviction Rate for Suspended Sentence	0.63	0.51
Sex Offences - Adult Conviction Rate for Community Sentence	2	0.78
Sex Offences - Adult Conviction Rate for Custody	5.57	1.72
Sex Offences - Adult Conviction Rate for Conditional Discharge	0.24	0.23
Sex Offences - Adult Conviction Rate for Fine	0.26	0.3
Sex Offences - Adult Conviction Rate for Suspended Sentence	0.63	0.51
Sex Offences - Juvenile Conviction Rate for Community Sentence	0.73	0.43
Sex Offences - Juvenile Conviction Rate for Custody	0.17	0.18
Robbery – Conviction Rate for Community Sentence	3.33	1.86
Robbery – Conviction Rate for Custody	11.58	7.03
Robbery – Conviction Rate for Conditional Discharge	0.04	0.16
Robbery – Conviction Rate for Fine	0.04	0.31

Robbery – Conviction Rate for Suspended Sentence	0.76	0.95
Robbery - Adult Conviction Rate for Community Sentence	0.7	0.75
Robbery - Adult Conviction Rate for Custody	9.87	6.6
Robbery - Adult Conviction Rate for Conditional Discharge	0.02	0.08
Robbery - Adult Conviction Rate for Fine	0.02	0.2
Robbery - Adult Conviction Rate for Suspended Sentence	0.76	0.95
Robbery - Juvenile Conviction Rate for Community Sentence	2.63	1.65
Robbery - Juvenile Conviction Rate for Custody	1.7	1.1
Property Crime – Conviction Rate for Community Sentence	1.64	0.58
Property Crime – Conviction Rate for Custody	0.99	0.35
Property Crime – Conviction Rate for Conditional Discharge	0.84	0.41
Property Crime – Conviction Rate for Fine	0.62	0.33
Property Crime – Conviction Rate for Suspended Sentence	0.23	0.2
Property Crime - Adult Conviction Rate for Community Sentence	1.14	0.47
Property Crime - Adult Conviction Rate for Custody	0.94	0.34
Property Crime - Adult Conviction Rate for Conditional Discharge	0.79	0.4
Property Crime - Adult Conviction Rate for Fine	0.6	0.32
Property Crime - Adult Conviction Rate for Suspended Sentence	0.23	0.2
Property Crime - Juvenile Conviction Rate for Community Sentence	0.5	0.18
Property Crime - Juvenile Conviction Rate for Custody	0.05	0.02
Property Crime - Juvenile Conviction Rate for Conditional Discharge	0.06	0.03
Property Crime - Juvenile Conviction Rate for Fine	0.02	0.02
Unemployment	5.85	2.2
Police Officer's Salaries	251.86	145.24
Youth 15 - 24	12.76	1.16

3.4 Total Number of Sentenced Offenders for Each Offence Type

For all crime categories, we established the total number of sentences issued to offenders for the period of 2002 - 2013. This gives us a clearer picture of what sentences are more dominant. It also allows us to see whether sentencing practices differ for adult and juvenile offenders. Figure 2 below illustrates a total number of offenders who received Absolute Discharge, Community Sentence, Conditional Discharge, Custody, Fine, Suspended Sentence and Otherwise Dealt With for the violence against the person crime category.

Figure 2: Total Number of Sentences Issued for Adult and Juvenile Offenders, Violence Against the Person, England and Wales, 2002 - 2013



The top part of the graph refers to adult offenders while the bottom part of the graph refers to juvenile offenders. The total number of sentences given to adults is much larger, as there are many more arrests for adult offenders than juvenile offenders (in the year ending March 2015 there were around 950,000 arrests for notifiable offences in England and Wales, of which 94,960 were of people aged 10-17 years.) The most common sentence type issued to adult offenders for these offence categories was custody while for juvenile offenders it was community sentence. Both of these sentences account for 73 per cent of total sentences issued, therefore, we can conclude that community sentence and custody are the most used sentences to offenders for violence against the person category. However, for adult offenders custody is more prevalent than community service whilst it is the other way round for the juvenile offenders. We now present the same break up across different crime types.

Figure 3: Total Number of Sentences Issued for Adult and Juvenile Offenders, Sex Offences, England and Wales, 2002 - 2013

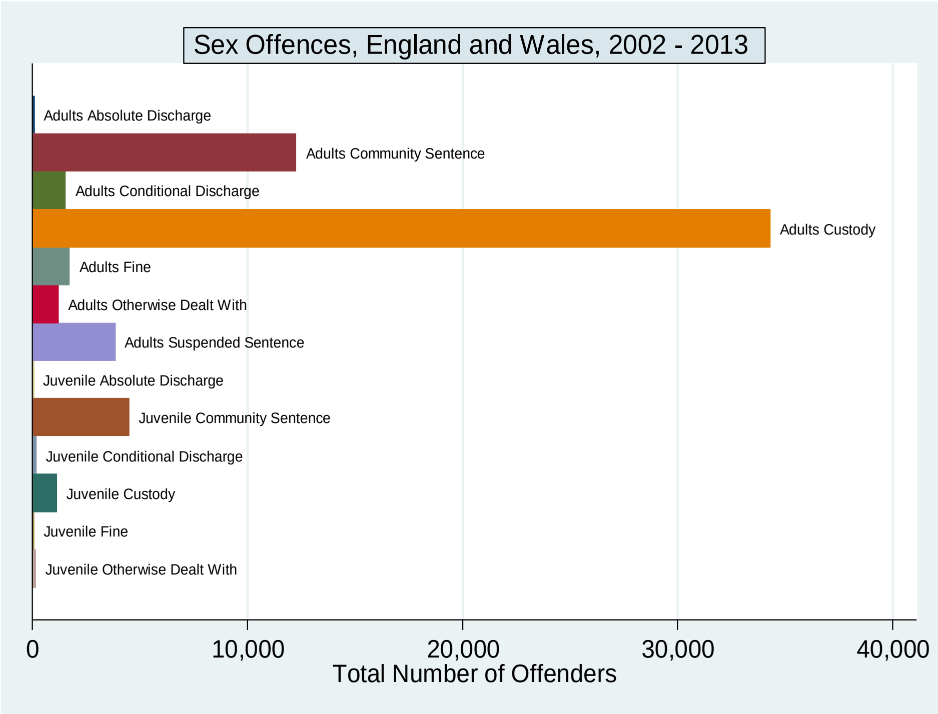


Figure 3 refers to the sex offences and illustrates how the sentences were distributed for adult and juvenile offenders. For the adult offenders, custody is by far the most dominant sentence with almost 35 thousand custody sentences issued over 2002 and 2013 followed by the community sentence with around 12 thousand sentences issued. Both violence against the person and sex offences have a very small number of absolute discharge sentences issued while fines and conditional discharges were used less. For the juvenile offenders, community sentence accounts for the largest number of the issued sentences followed by custody. Same as with the adult offenders absolute discharge, conditional discharge and fines do not account for a large number of the total sentences.

Figure 4: Total Number of Sentences Issued for Adult and Juvenile Offenders, Robbery, England and Wales, 2002 - 2013

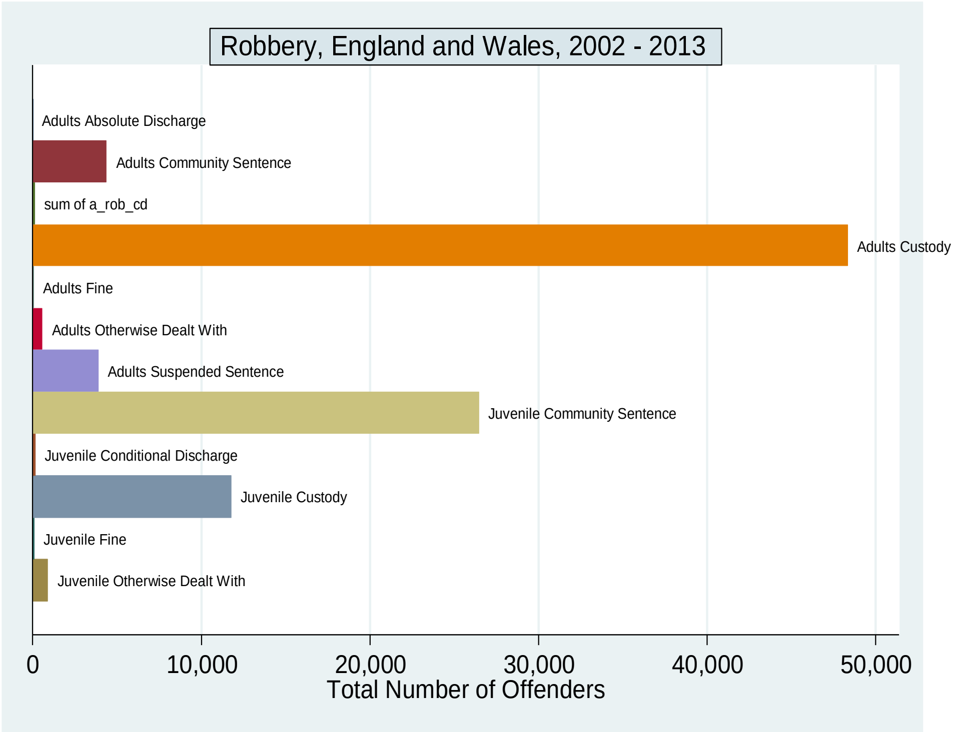
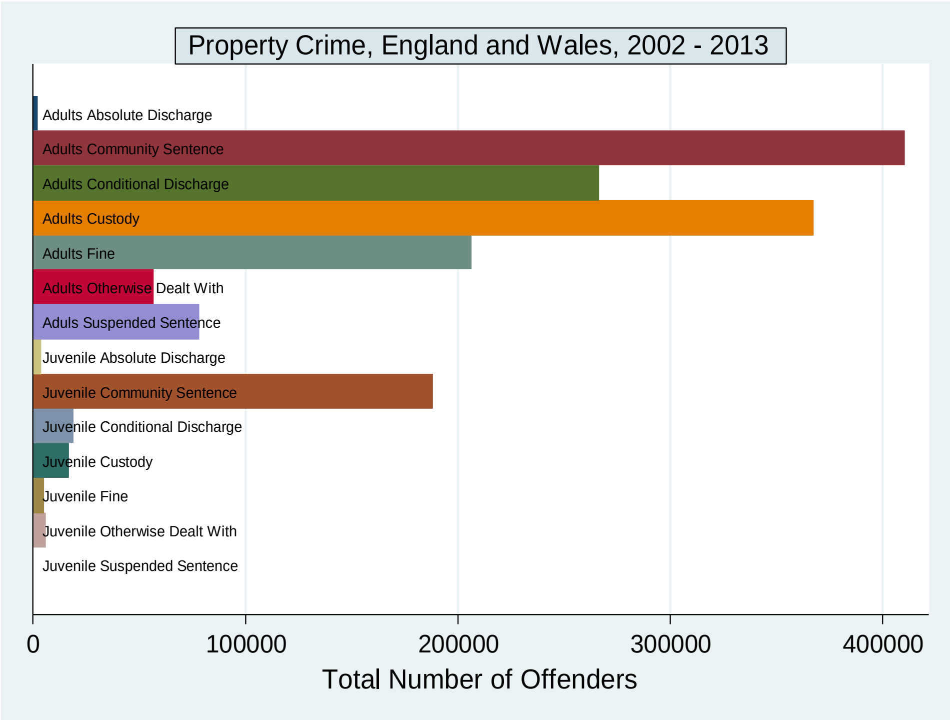


Figure 4 above refers to robberies and how many sentences were issued to adult and juvenile offenders for the given time period. Same as with the other two violent crimes (violence against the person and sex offences) for adult offenders custody is by far the most prevalent sentence accounting for almost 85 per cent of the total sentences issued to adult offenders for robbery. Community sentence came second with just under 8 per cent of the total sentences issued. For juvenile offenders two thirds received community sentence while just under 30 per cent received custody and all other types of sentences accounted for less than 3 per cent. Overall, we can observe the same trend with all three violent crime types for adult and juvenile offenders. There are more adult offenders receiving custody than community sentence and there are more juvenile offenders receiving community sentence than custody.

Figure 5: Total Number of Sentences Issued for Adult and Juvenile Offenders, Property Crime, England and Wales, 2002 – 2013



For Property crime, we can see from the Figure 5 above that for adult offenders sentencing becomes more diverse. Community sentence accounts for the largest number of sentences issued followed by the custody and conditional discharge. Whilst absolute discharge still remains in low numbers, we can see that there are more fines being issued. Community sentence is the most prevalent for juvenile offenders, conditional discharge is second while custody is third by the number of sentences issued. The main difference in property crime with regards to the sentences issued is that for adult offenders community sentence is used more often than custody which is opposite to the violent crimes mentioned above. Moreover, other non-custodial sentences are used more than in violent crime cases.

3.5 Empirical model

The econometric specification of our main model is as follows:

$$CrimeRate_{i,t} = \beta_1 CommunitySent_{i,t-1} + \beta_2 Custody_{i,t-1} + \beta_3 ConditionalDischarge_{i,t-1} + \beta_4 Fine_{i,t-1} + \beta_5 SuspendedSentence_{i,t-1} + \beta_6 PoliceOfficersSalaries_{i,t} + \beta_7 Unempl_{i,t} + \beta_8 Youth_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t} \tag{3}$$

where i represents the Police Force Authority, t represents time, σ_i is the unknown intercept for each PFA, μ_t represents year fixed effects which are needed to account for PFA specific year changes, and $\varepsilon_{i,t}$ is the error term. The explanatory variables, *CommunitySent* stands for the conviction rate for all offenders who got sentenced with a community sentence, *Custody* is the conviction rate for all offenders who got issued a custodial sentence, *ConditionalDischarge* is the conviction rate for all offenders who received conditional discharge as a sentence for the crime they have committed, *Fine* is the conviction rate for the offenders who were fined, *SuspendedSentence* is the conviction rate for all offenders who received suspended sentence. Also, *PoliceOfficersSalaries* stands for total cost of police salaries, *Unempl* for unemployment rate and *Youth* for the ratio of people aged 15 to 24 in the population.

We are using PFA level fixed effects in order to eliminate unobserved area-specific time-invariant effects and thus controlling for the average differences across PFAs for any observable or unobservable predictors, such as differences in size, characteristics and many others. In that way, the fixed effect coefficients control for all the across-PFA variation and we are left with the within-PFA variation, which helps us greatly reduce the problem of omitted variable bias. We also include fixed time effects into our estimation model as the year dummies pick up any variation in the outcome that happen over time and that is not attributed to our other explanatory variables.

For conviction rates we are using lagged variables in order to minimise possible issues with the endogeneity which arises due to possible reverse causality between our dependent variable – crime rate – and conviction rate as both of them can have an effect on each other. Hence, including a time lag on conviction rate minimises the effect since crime rate this year cannot affect the conviction rate last year.

Also, alongside our main model, we want to test the relationship between crime rate and conviction rates for adult and juvenile offenders separately. We keep the rest of the model the same. However, since sentences issued to the offenders for violent crimes and property crime vary and there are more non-custodial sentences used for both adult and juvenile offenders for property crime offences, the econometric specification slightly differs between violent and property crimes as we include more non-custodial sentences for juvenile offenders in the latter.

Econometric specification of the model for violence against the person, robbery and sex offences is as follows:

$$CrimeRate_{i,t} = \beta_1 AConvictionCS_{i,t-1} + \beta_2 AConvictionCust_{i,t-1} + \beta_3 AConvictionCD_{i,t-1} + \beta_4 AConvictionF_{i,t-1} + \beta_5 AConvictionSS_{i,t-1} + \beta_6 JConvictionCS_{i,t-1} + \beta_7 JConvictionCust_{i,t-1} + \beta_8 PoliceOfficersSalaries_{i,t} + \beta_9 Unempl_{i,t} + \beta_9 Youth_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t} \tag{4}$$

where i represents the cross-section unit of observation, t represents time, σ_i is the unknown intercept for each PFA, μ_t represents year fixed effects which are needed to account for PFA specific year changes, and $\varepsilon_{i,t}$ is the error term. As for explanatory variables, *AConvictionCS* stands for the conviction rate for adults who got sentenced with a community sentence, *AConvictionCust* is the conviction rate for adults who got issued a custody, *AConvictionCD* is the conviction rate for adults who received conditional discharge as a sentence for the crime they have committed, *AConvictionF* is the conviction rate for the adults offenders who were fined, *AConvictionSS* is the conviction rate for adults offenders who received suspended sentence, *JConvictionCS* is the conviction rate for juvenile offenders who got sentenced with a community sentence and *JConvictionCust* is the conviction rate for juvenile offenders who got issued a custody.

For property crime econometric specification is as follows:

$$CrimeRate_{i,t} = \beta_1 AConvictionCSi_{,t-1} + \beta_2 AConvictionCusti_{,t-1} + \beta_3 AConvictionCD_{i,t-1} + \beta_4 AConvictionF_{i,t-1} + \beta_5 AConvictionSS_{i,t-1} + \beta_6 JConvictionCS_{i,t-1} + \beta_7 JConvictionCust_{i,t-1} + \beta_8 JConvictionCD_{i,t-1} + \beta_9 JConvictionF_{i,t-1} + \beta_8 PoliceOfficersSalaries_{i,t} + \beta_9 Unempl_{i,t} + \beta_9 Youth_{i,t} \ _{,t} + \sigma_i + \mu_t + \varepsilon_{i,t}$$

Everything else being the same as in the model above we also include conviction rate for juvenile offenders who got conditional discharge which is labelled as *JConvictionCD* and conviction rate for juvenile offenders who were fined for the property crime offences they have committed which is labelled as *JConvictionF*.

3.6 Results

The empirical results of our main model are presented in the Table 8 below. They are presented in the elasticity form which was derived from level-level coefficients (Appendix B.5) using sample means in order to make the interpretation easier.

Table 8: Fixed effects regression models	VATP	Sex Offences	Robbery	Property Crime
Conviction Rate for Community Sentence (t-1)	-0.04	-0.03	**-0.1*** **	**-0.2*** **
Conviction Rate for Custody (t-1)	**-0.2*** **	**-0.12*** **	0.05	**-0.15** **
Conviction Rate for Conditional Discharge (t-1)	-0.01	**-0.001** **	-0.0009	0.04
Conviction Rate for Fine (t-1)	0.01	0.0004	0.004	**0.06** **
Conviction Rate for Suspended Sentence (t-1)	-0.03	-0.02	0.03	0.00008
Police Officers' Salaries	0.0008	0.03	0.01	0.0007
Unemployment	**-0.12** **	-0.06	**-0.39* **	**-0.14*** **
Youth 15 - 24	-0.23	-0.27	**1.4** **	**0.41** **
Fixed Time Effects	Yes	Yes	Yes	Yes
Number of Observations	462	462	462	462
R^2 (within)	0.71	0.4	0.51	0.9

Note: dependent variable is the crime rate per 1000 people. Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively. Results are converted to elasticity form using sample means from the level-level results reported in the Appendix B.5. Robust Standard errors are reported in the Appendix B.5.

For violence against the person offences the conviction rate for community sentence has a negative but insignificant effect of 0.04%. However, the conviction rate for the custody has a negative and significant coefficient. A 1% increase in the conviction rate for the custody would reduce crime rate by 0.2%. Coefficients of the conviction rates for conditional discharge and suspended sentence are both negative but insignificant and the coefficient of the conviction rate for fines is positive but insignificant.

For sex offences, the conviction rate for community sentence is negative but insignificant as was the case for violence against the person. However, custody has negative and significant effect on sexual offences rate suggesting that a 1% increase in the conviction rate for custody would reduce crime rate by

0.12%. This is a similar finding to the one we found for the violence against the person crime rates. The effect of conditional discharge is different as for sexual offences the effect is negative and significant. A 1% increase in the conviction rate for conditional discharge would reduce crime rate by 0.001%. Conviction rates for fine and suspended sentence are positive and negative respectively but both are insignificant.

For robbery offences, the impact of more convictions leading to a community sentence is negative and significant. A 1% increase in the conviction rate for community sentence reduces crime rate by 0.1%. The conviction rate for the custody is positive and insignificant and that is the opposite effect that we found for the violence against the person and sexual offences. This suggests that sentencing types can have different effects on different crime types. For example, if community sentence is not an effective way to combat one crime type it does not mean that it will not be effective for a different offence category. Other conviction rates for sentencing are insignificant.

For property offences, which is the only economic crime type in our analysis, both conviction rates for the community sentence and for the custody are significant and negative. A 1% increase in the conviction rate for the community sentence would reduce crime rate by 0.2% while a 1% increase in the conviction rate for the custody would reduce it by 0.15%. This suggests that alternatives to custody can sometimes be more effective than incarceration. Conviction rates for the conditional discharge and suspended sentence are both insignificant. However, conviction rate for fines is positive and significant. It shows that a 1% increase in the conviction rate for the fine would increase property crime rate by 0.06%. Since it is an economically motivated crime, it is possible that paying fines reduces the offender's income. Therefore, more crime could be encouraged thereafter in order to compensate for the financial losses fines have imposed.

Other explanatory variables - unemployment, police officers' salaries and proportion of youth in the population – were also included in our analysis. For violence against the person offences only unemployment has a significant effect of 0.12% reduction if increased by 1%. For sex offences all of the variables are insignificant. For robbery offences unemployment has a negative and significant coefficient, a 1% increase in unemployment reducing crime rate by 0.39%. Also, the youth variable is positive and significant. A 1% increase in youth population would increase robbery rate by 1.4%. This is different from violence against the person and sexual offences. This may reflect the different economic motivations associated with robbery compared to other forms of violence. For property crime, unemployment has a negative and significant co-efficient, a 1% increase in unemployment would reduce crime by 0.14%. The youth variable is positive and significant and it suggests that a 1% increase in youth population would increase property crime rate by 0.41%. Youth variable has an effect predicted by the theory due to lower opportunity costs for the younger people. Younger people on average earn less and if caught would have less to lose in earnings than older population.

Also, young offenders often receive more lenient punishment. As for unemployment, Ehrlich (1973) argues that its effect on crime in ambiguous and unemployment has both motivation and opportunity effects as explained by Cantor and Land (1985). Opportunities to commit crime decrease when more people are out of job – less opportunities to commit a crime in a workplace and more time to guard your home during the day (see Bandyopadhyay et al. (2012) for fraud and robbery). Also, economic theory emphasises the economic attractiveness of an area to potential offenders suggesting some crime spillover effects across the areas.

Overall our results suggest that alternatives to custody can be as effective in reducing crime rates as incarceration. However, there is variance between crime types. Violent and sexual offences are more affected by the custodial sentences while robbery and property crime can be managed at least as effectively by the community sentences based on our findings. Economic and non-economic crimes could have a different motivation by the offenders who committed these crimes and with the aggregate data we are unable to separate general deterrence effect from incapacitation effect but our results suggest that alternatives to custody can work more effectively on economic crimes such as property crime (robbery is classified as a violent crime but does not always contain a violence) than on violent crimes such as violence against the person and sexual offences.

Table 9 below reports our findings about the relationship between crime rates and conviction rates for adult and juvenile offenders separately. As with the main results table, these results are presented in the elasticity form which was derived from level-level coefficients (Appendix B.6) using sample means in order to make the interpretation easier.

Table 9: Fixed effects regression models for adult and juvenile offenders	VATP	Sex Offences	Robbery	Property Crime
Adult Conviction Rate for Community Sentence (t-1)	0.02	-0.02	**-0.02***	**-0.16*****
Adult Conviction Rate for Custody (t-1)	**-0.16*****	**-0.13*****	**0.06***	**-0.12****
Adult Conviction Rate for Conditional Discharge (t-1)	**-0.05****	**-0.02****	0.0015	0.03
Adult Conviction Rate for Fine (t-1)	**-0.03***	0.005	0.0002	**0.06***
Adult Conviction Rate for Suspended Sentence (t-1)	**-0.09*****	-0.01	0.02	0.02
Juvenile Conviction Rate for Community Sentence (t-1)	-0.003	-0.02	**-0.06****	0.009
Juvenile Conviction Rate for Custody (t-1)	**-0.03****	0.01	-0.02	-0.02
Juvenile Conviction Rate for Conditional Discharge (t-1)				-0.005
Juvenile Conviction Rate for Fine (t-1)				**-0.02*****
Police Officers' Salaries	-0.005	0.02	0.02	0.01
Unemployment	**-0.12****	-0.08	**-0.39***	**-0.14*****
Youth (15 – 24)	-0.2	-0.27	**1.26****	**0.34***
Fixed Time Effects	Yes	Yes	Yes	Yes
Number of Observations	462	462	462	462
R^2 (within)	0.74	0.4	0.51	0.9

Note: dependent variable is the crime rate per 1000 people. Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively. Results are converted to elasticity form using sample means from the level-

level results reported in the Appendix B.6. Robust Standard errors are reported in the Appendix B.6.

The results for adult and juvenile offenders show that community sentences are more effective on adult than on juvenile offenders when it comes to addressing property crime. In our main specification, the effect was negative and significant for robbery and property crimes. However, while holding for the adult offenders for both crime types, the results lose significance for robbery for juvenile offenders. Results differ when it comes to custody. In our main specification, custody showed a negative effect on violence, sexual offences and property crime. The effects for these crimes are the same for adult offenders. But for juvenile offenders only custody for violence against the person has any significant impact, and the effect on sex offences and property crime becomes insignificant.

On the other hand, the conviction rate for the custody for adult offenders now has a positive and significant effect on robbery offences showing that a 1% increase in the conviction rate for the custody would increase robbery rate by 0.06%. Once offenders are separated by adults and juveniles the alternatives to custody show more impact on the violent crimes. In the main specification, only custody was significant. For adult offenders taken separately, however, the conviction rates of the conditional discharge, fines and suspended sentence became negative and significant showing that the increase of a 1% of those conviction rates would lower the crime rate by 0.05%, 0.03% and 0.09% respectively. Overall, these results show, like our main model, that alternatives to custody can work effectively to reduce crime. In addition, adult and juvenile offenders react differently to changes in sentencing. Whilst none of the results became significant for juvenile offenders from what was already significant in the main specification, there were changes for adult offenders where more alternatives to custody sentencing became significant for reducing crime rates.

3.7 Robustness checks

3.7.1 Impact of financial crisis on the crime-sentencing relationship

For robustness analysis, we want to check whether our model coefficients are stable when we consider the possible implication of the financial crisis in 2008 – 2009. Campos et al (2010) investigates the impact of the recession on people's lives at a regional level in the UK. They find that unemployment levels were adversely affected by the recession at different times and each area with West Midlands and North West regions having the largest rises in the unemployment rate. While redundancy rate rose across all English regions, workforce jobs decreased and the rate of change of basic earnings fell continuously, criminal justice agencies faced significant budget cuts and the Coalition government's 2010 spending review called for police budgets to be reduced by 20 per cent (Millie and Bulllock, 2012). Budget cuts led to widespread debate by public and politicians regarding what is realistically expected of the police and what they can actually deliver. Government emphasised "Big Society" project – political ideology where a significant amount of responsibility for how our society runs is devolved to local communities and volunteers - that the private sector, volunteers and community groups would step up to fill any void. Therefore, post-recession years proved to be particularly challenging for the police services. With rising unemployment, falling incomes and lower police budgets, they were asked to deliver the same level of service to the public.

In order to test if our model's results are robust to including the impact of the financial crisis, we include a dummy variable for post-recession years (>2007) and interactions of all explanatory variables with that dummy and the rest as before:

$$CrimeRate_{i,t} = \beta X + \sigma_1 RecessionDummy + \sigma_2 RecessionDummy*X + \sigma_i + \varepsilon_{i,t}$$

All variables are the same as in the main model stated above. X defines a set of explanatory variables as before. Recession dummy is set to be equal to 0 for years up to 2008 and from 2008 it is set to be equal to 1. We would interpret σ as a level shift change in crime, for example, a positive coefficient would show that there was a level increase in crime in post-recession years.

Appendix B.7 contains detailed results of the empirical models tested above. The recession dummy itself is positive and significant for all crime categories, which implies that crime rate has experienced a level shift as a result of financial crisis. Most of the interaction dummies for various sentencing types are not statistically significant suggesting that marginal impact of various sentencing types does not vary across different phases of the business cycle. The signs and size of the main coefficients when compared to our main models for violent and property crimes do not change much with the conviction rate for custody showing a negative impact on crime for all violent crimes and the conviction rate for community sentence showing a negative effect on robbery and property crimes.

3.7.2 Lagged specification

We changed the contemporaneous socio-economic variables in the main model to the one period lagged values of these variables and estimated a new model in a form of:

$$CrimeRate_{i,t} = \beta_1 CommunitySent_{i,t-1} + \beta_2 Custody_{i,t-1} + \beta_3 ConditionalDischarge_{i,t-1} + \beta_4 Fine_{i,t-1} + \beta_5 SuspendedSentence_{i,t-1} + \beta_8 PoliceOfficersSalaries_{i,t-1} + \beta_9 Unempl_{i,t-1} + \beta_9 Youth_{i,t-1} + \sigma_i + \mu_t + \varepsilon_{i,t}$$

All variables are the same as in the main model stated above. This specification addresses the potential issue of these variables affecting crime rate with a lag. The results are similar to the main results reported earlier (detailed results are available in the Appendix B.8). The impact of community sentences remains significant. Robbery and property crimes both have negative and significant effects of -0.11% and -0.22% respectively. The conviction rate for custody remains significant for violence against the person (-.21%), sexual offences (-

0.12%) and property crime (-0.14%). However, it remains positive but becomes insignificant for robbery. Fines remain significant for property crime with a coefficient of 0.06% suggesting they are an ineffective way of reducing property crime. Conditional discharge remains negative and significant for sexual offences (-0.02%). On the whole, results are similar to our main findings and community sentences remain significant for particular offence types.

3.7.3 Cross crime sentencing effects

Criminologists identify a few types of crime displacement that can take place (Barr and Pease, 1990; Gabor, 1981). One of them is when criminals decide to shift to another type of crime when a crime control program is implemented. It suggests that higher conviction rates for one crime type can shift offenders from one crime type to another. On the other hand there is a counter-argument that in fact there is very little displacement and instead crime control programmes have a general crime lowering or 'diffusion effect'. In our new model[10], the explanatory variables for each crime category are conviction rates for sentencing for all other crime types but the one tested.

Full results table is reported in the Appendix B.10. For violence against the person, our findings suggest that a 1% increase in the conviction rate for custody and suspended sentence for sex offences, would reduce the crime rate

[10] Appendix B.9

by 0.06% and 0.03% respectively. However, the same increase in the conviction rate for fines for property crime, would increase it by 0.07%.

For sex offences, the conviction rate for suspended sentence for violence against the person has a positive and significant effect of 0.06% if it was increased by 1%. This suggests that if more suspended sentences were issued for violent crimes, there would be more sex offences recorded a year later. Also, a 1% increase in the conviction rate for the community sentence for robbery offences and the conviction rate for the suspended sentence for the property crime both have a negative and significant effect reducing sex offences rate by 0.04% and 0.1% respectively.

For robbery, a 1% increase in the conviction rates for community sentences (as well as conditional discharges for sex offences) could lower the robbery rate as both have negative and significant effects of -0.09% and -0.03% respectively. Also, the conviction rate for the community sentence for property crime has a negative and significant effect on the robbery rate which suggests that if more community sentences were issued for property crime last year, less robbery offences were recorded this year. This finding is also true in the reverse, or in other words, the relationship between conviction rate for the community sentence for robbery offences and the property crime rate is also negative and significant. Hence, it suggests that more community sentences for robbery in the previous would lead to less property crime recorded the next year. The conviction rates for conditional discharges and fines for the property crime both have positive and significant effect on the robbery rate showing that an increase of 1% would result in 0.27% more robbery offences recorded for the conditional discharge and 0.22% more for the fines. In our main model we found that the conviction rate for fines for property crimes had a positive and significant effect on property crime rate. This analysis also shows that issuing more fines for property crimes could lead to an increase in other crime rates as well. This suggest fines have an unfavourable impact, causing more crimes of other categories as a result.

For property crime, a 1% increase of the conviction rate for the custody for the violence against the person offences would reduce property crime rate by 0.12%, a 1% increase of the conviction rate for the suspended sentence for sex offences would decrease it by 0.02% and a 1% increase in the conviction rate for the community sentence for robbery would reduce it by 0.02%. Also, a 1 % increase of the conviction rate for the suspended sentence for the robbery offences has a positive and significant effect of 0.01%. The effects of socio-economic variables remain consistent with the findings in our main model. These results suggest that criminals can indeed change what type of crime they choose to commit, however, at the same time higher conviction rates for other crime categories (barring fines) can deter offenders from committing other types of offences, suggesting more of a diffusion than displacement effect in general.

3.8 Discussion

Our results suggest that while custody is an effective way of reducing crime it is not the only way to do so. Also, it is important to note that custody can sometimes have a detrimental effect on crime. In our study robbery has a positive and significant relationship with the adult conviction rate for custody suggesting that, in fact, the robbery rate increases if more offenders are sentenced to custody. This shows that criminogenic effects for adult offenders in custody for robbery might be stronger than for violence against the person, sex offences and property crime. For them custody had a negative impact on the crime rate. Alternative sentences such as community sentence and conditional discharge also reduced crime rates for all three violent crimes (property crime here is an exception as fines for adult offenders had a positive effect on crime rates) suggesting that crime can be reduced by routes other than prison. In order to illustrate how a 1% increase in the conviction rate affects total number of offences we have calculated the following for the adult offenders based on the recorded crime in the UK in 2014:

Table 10: Number of offences of violent crimes could be changed by changing the type of sentencing issued by 1 per cent			
Offence type	**Violence Against the Person**	**Robbery**	**Sexual Offences**
Total number of offences recorded by the police (by adult offenders)	720833	48585	78609
Estimated change in a number of offences after 1% increase in custody[11]	-1153	+29	-102
Estimated change in a number of offences after 1% increase in community sentence		-10	
Estimated change in a number of offences after 1% increase in conditional discharge	-360		-16
Estimated change in a number of offences after 1% increase in suspended sentence	-649		

We can see, for Violence Against the Person, that more than 1000 offences would be prevented if there was a 1% increase in the conviction rate for custody (for adult offenders). However, almost the same number of offences could be prevented if there was 1% increase in conditional discharges and 1% increase in suspended sentences. For robbery, no such impact from additional sentencing is found. This could reflect its economic motivation in contrast to

[11] All these estimated are based on the data for 2013-2014 crime trends from https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/bulletins/crimeinenglandandwales/2015-04-23 and https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/399379/youth-justice-annual-stats-13-14.pdf

other violent crimes. 98% of sexual offence convictions result from crimes committed by adult offenders. Increases in both custody and conditional discharges prevent further offences. However, a 1% increase in the conviction rate for custody for adult offenders prevents over six times more offences than 1% increase in the conviction rate for conditional discharge.

Table 11 below illustrates estimated effects of sentencing 1% more adult offenders to custody and community sentence in terms of prevented offences.

Table 11: Number of offences of property crimes could be changed by changing the type of sentencing issued by 1 per cent

Property Crime	Custody	Community Sentence
Estimated change in a number of offences[12]	-2693	-3590

Note: Estimated impact of sentencing 1 per cent more offenders to each sentence type on number of recorded crimes in 2014 for adult offenders

While both community sentence and custody are effective at reducing property crime, community sentence are more effective. These illustrative findings suggest that while prison can work in combating illegal activities for certain crime types, alternatives to custody can also achieve that while costing much less.

[12] All these estimated are based on the data for 2013-2014 crime trends from https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/bulletins/crimeinenglandandwales/2015-04-23 and https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/399379/youth-justice-annual-stats-13-14.pdf

3.9 Conclusion

This study explores the question of whether and which alternatives to custody can substitute for incarceration. We focus on England and Wales, a region with one of the highest prison populations in Europe and where recent policy has tried to reduce reliance on incarceration. We identify a hitherto unused dataset on sentencing practice at the Police Force Area level. This is in contrast both to other studies that focus on aggregate measures such as prison population to measure variation in sentencing regimes, and to individual-level studies that are unable to explore the impact of different sentencing approaches on a population of offenders and the general public.

We find that for some offence types, there are credible alternatives to custody that are either superior or approximately equivalent to a prison sentence in terms of impact on the local crime rate. However, what that alternative is depends on the type of offence and, also, whether the offender is adult or juvenile. Since custody typically costs more than alternatives (besides the significant social disadvantages), our results suggest that there is scope to provide for public protection through the criminal justice system more efficiently and humanely than the status quo. The results also suggest that policies implementing alternatives to custody in the United Kingdom have already produced moderate success in terms of offering credible alternatives to sentencing judges, even though they have not yet significantly reduced reliance on incarceration as a criminal justice strategy.

4. Does Community Resolution reduce reoffending?

4.1 Introduction

A growing body of research on the effects of criminalisation[13] coupled with demands on law enforcement and prison agencies has led to recent extensions of the use of professional judgement-led forms of justice. Community Resolution provides an opportunity for the police to deal with appropriate low offences and offenders. As stated in the *Guidelines on the use of Community Resolutions (CR) Incorporating Restorative Justice (RJ)* "A Community Resolution is the nationally recognised term for the resolution of a less serious offence or anti-social behaviour incident, where an offender has been identified, through informal agreement between the parties involved as opposed to progression through the traditional criminal justice process". CR allows the police to make decisions about how to deal more proportionately with lower level crimes and it is focused at first time offenders who showed genuine remorse, and where the victim (if there is one) has agreed that the police do not take more formal action. The form in which CR could take place would include a simple apology, an offer of compensation for the damage caused or a promise to clear up criminal damage. It offers victims an informal and flexible response to the crime they have reported and it allows victims to have a say in how it is dealt with. This is in line with the understanding that some victims want a simple outcome to the matter they reported which does not involve formal

[13] See Andersen (2015), Cid (2009), Drago et al. (2009)

criminal justice processing. At the same time Community Resolutions allow offenders to correct their mistakes without suffering the consequences of a criminal record which could strongly affect future life chances. It provides an opportunity to evaluate the impact they have caused on victims, make amends and learn from the experience on just how close they were to facing a full judicial process. Also, whilst CR does not result in a criminal record on the Police National Computer, it is still recorded on police information systems and a previous case of CR would be taken into account if further offences were committed. The potential benefits of this approach are both short run in nature (short investigation, lower police costs) as well as more long-term (reduced long-term offending e.g. a disposal such as CR avoids the so-called criminogenic effect that prison entails (Killas et al., 2010, Nieuwbeerta et al., 2009)).

It is important to note that while CR can incorporate a spectrum of activities including restorative justice, it does not mean that every CR incorporates the use of restorative justice. The main difference between the two is that while CR is appropriate for low level offences, restorative justice can be appropriate with more serious crime when used alongside prosecution and/or appropriate sentence including prison. In other words, restorative justice is not a disposal[14] (while CR is) and can be used at any stage of the criminal justice system alongside or as part of a sentence for any level of crime. There is evidence that

[14]Disposal means an out of court police disposal which is a way of dealing with less serious offending by the police.

these terms are sometimes used incorrectly by interchanging the terms community resolution and restorative justice (see Wesmarland et al., 2018) and an article on Restorative Justice Council website[15]) which can mislead the public.

In short, Community Resolutions provide the police with a timely and effective way to deal with lower level crime and anti-social incidents reported. However, one of the other benefits of CRs as listed in the *Guidelines on the use of Community Resolutions (CR) Incorporating Restorative Justice (RJ)* is the reduction of the likelihood of reoffending by encouraging offenders to face up to the impact of their actions and to take responsibility for making good the harm caused.

In this chapter we use data collected by Norfolk and Suffolk Police on case disposals from 2010 to 2014, with the aim of evaluating the effectiveness of CR when compared to other forms of police outcomes such as cautions, being charged, being issued with a warning or penalty notice. In order to do that, we analyse the effect of CR on overall reoffending rates and on time to reoffending (for 4 different time intervals). We compare reoffending rates of the offenders for whom CR is the outcome recorded by the police to other outcomes for 'similar' offences and offenders. According to the latest

[15] https://restorativejustice.org.uk/news/community-resolution-and-restorative-justice (accessed 14th March 2019)

publication on proven reoffending by the Ministry of Justice National Statistics[16], reoffending rates remain high in the UK for both adult and juvenile offenders. Therefore, it is important to understand what works and where. In particular, if CR works, this would reduce reoffending rates and potentially reduce the need for prison.

The methodology we employ is a well-known quasi-experimental design called *Propensity Score Matching* which is widely used in the criminology literature. Propensity Score Matching has been used to look at other criminal justice outcomes e.g. whether prison based education affects recidivism (Kim and Clark, 2013, Lichtenberger, 2007, Gaes, 2008), how custody impacts reoffending (Jolliffe and Hedderman, 2015), the impact of substance use and drinking on future crime rates for young people (Craig et al., 2015, Slade et al., 2008) and the relationship between gang membership and violent victimization (Gibson et al, 2009). In this analysis we use it to test whether community resolution affects reoffending rates. We then further analyse the impact of CR on recidivism by employing a survival analysis method. It controls for the amount of at-risk time each offender had while in community as we are using the actual date of when recidivism took place as the outcome variable. Since the time to reoffence is an interest of this study, we took the length of at-risk time into consideration and conducted a survival analysis

16 https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/676431/proven-reoffending-bulletin-jan16-mar16.pdf

where offenders who were matched using the PSM method were analysed in the proportional hazard ratio model (Cox regression). It addressed the issue of how quickly matched groups reoffended after having their first offence recorded. Our findings show that CR can significantly reduce reoffending rates and time to reoffending.

4.2 Related Literature

Recidivism and effective ways to prevent recidivism have been a topic to explore by social scientists, criminologists and law specialists for many years. Whilst Community Resolutions are not widely explored in the literature yet (apart from Wesmarland et al., 2018) which focuses on out of court resolutions in policing domestic violence and abuse in the United Kingdom) there are studies exploring the impact of other sentencing types and various treatments received by the offenders on their reoffending rates. There are studies that use panel level data (Abramovaite et al., 2018, Durlauf and Nagin, 2010, Vieratis et al., 2007, Saridakis and Spengler, 2012) to analyse various effects on crime rates and there are studies that use individual level data. Propensity Score Matching and Survival Analysis methods are both widely used in the later.

Jolliffe and Hedderman (2015) used a dataset of 5,500 male offenders from 1 of 10 regions in the United Kingdom to investigate the impact of custody on reoffending using propensity score matching. Their results suggest that 1 year after release offenders who had been sent to prison were significantly more likely to have committed another (proven offence). In Netherlands, Wermink et al. (2010) used longitudinal official record data on 4,246 adult offenders to compare recidivism for a period up to eight years after community service to that after short-term prison sentence. By controlling for a large set of confounding variables and using matching method they show that offenders reoffend significantly less after having received community service compared to after having been imprisoned. Their results are robust for both the short and long term.

However, some slightly older studies did not always find similar support for community sentences. Smith and Akers (1993) analysed recidivism of Florida's Community Control and prison using survival analysis. They used a small sample of male offenders from Community Control and prison who were matched on four covariates, however, both groups differed significantly on race and prior felonies, with the prison group having a larger proportion of non-white offenders and offenders with prior felonies. Their findings show that recidivism rates and survival curves of both groups were essentially the same and around 4 out of 6 offenders sentenced to Community Control or prison reoffended during the five year study. Wesiburd et al. (1995) examined the impact of sanctions on the criminal careers of 742 offenders convicted of white-collar crimes in seven US district courts between 1976 and 1978. They matched prison and non-prison groups in terms of factors that led to them receiving a prison sentence such as criminal history or crime arrested for and personal circumstances. They found that both groups had no significant difference in reoffending rates in the 126 months follow up period.

There are also a number of studies (Saylor and Gaes, 1997, Lichternberger, 2007, Kim and Clark, 2013) which focus on work experience and/or educational training whilst in custody and on how it affects reoffending once released from prison.

Sayor and Gaes (1997) used data collected by the Post-Release Employment Project in the US which was designed to evaluate the impact of any work related training or work experience on an offender's behaviour following release from prison. Data were collected from 1983 till October 1987 on over 7,000 offenders. They have looked at several behavioural outcomes including long term reoffending and found that offenders who were in prison and worked there were 24 percent less likely to reoffend throughout the observation period (reoffending data were collected in 1995 meaning that follow up data on reoffending data ranged from 8 to 12 years depending on release date) and those who participated in either vocational or apprenticeship training were 33 percent less likely to reoffend.

Lichtenberger (2007) matched offenders from the fiscal year 1999, 2000, 2001 and 2002 release cohorts on their marital status, offence type, custody code at release and other eight characteristics to observe if there is any difference on vocational programs in Virginia on post-release outcomes for full completers. He used propensity score model to match non-participants to the vocational completers and compared their earnings. At the end of study period (fiscal year release cohorts 1999 – 2002 combined) earnings of the full completers were almost 24 per cent higher than those of control group.

Kim and Clark (2013) in their study on the effect of prison-based college education programs in New York State on reoffending focus on self-selection bias when measuring recidivism and, therefore, are using Propensity Score Matching method to control for it. They find that the reoffending rates are significantly lower for the offenders who completed college program and that reoffending rate for a comparison group which was not derived using the PSM method was more than double the rate which was derived using the PSM method. This finding highlights the need to use appropriate techniques to control for selection-bias when measuring the effect of education programs on recidivism.

Other studies utilised PSM or Survival Analysis to analyse a range of questions in crime literature.

Craig et al. (2015) used PSM to estimate the impact of heavy drinking on criminal convictions occurring in early adulthood. Using data from England and Wales with dependant variable being conviction rates and primary independent variable being heavy drinking authors found that heavy drinkers were significantly more likely to be convicted for crimes in early adulthood when compared to those who did not engage in heavy drinking. Cloyes et al. (2010) utilised survival analysis to demonstrate a significant difference in return rates and community tenure for offenders in Utah State with serious mental illness compared to offenders without serious mental illness when controlling for demographics, condition of release, offence type and condition of return. Baglivio et al. (2014) used PSM to compare the effectiveness of Multisystemic Therapy with Functional Family Therapy using a multiyear state wide sample of juvenile offenders. Both therapies are designed to help youth to function better at their homes, schools and communities. They used data on 2,312 juvenile offenders drawn from Florida Department of Juvenile Justice and one of the outcome variables used was reoffending rates within 12 months. They report few significant differences in the effectiveness of both therapies. Ostermann (2015) used Cox proportional hazards survival tests to analyse the post release performance of former inmates who were released from a prison in New Jersey in 2006. Results indicated that after around 3 years after release, those who were released to supervision were involved in less new crimes when compared to those who were released unconditionally. However, there was still a high proportion of those released to supervision who reoffended shortly after their release and the predicted probability on recidivism did not differ substantially between both release groups.

4.3 Propensity Score Matching

The main purpose of this analysis is to learn whether or not community resolution as a police outcome on offenders has any negative (reducing) effect on further offending by those offenders. Whilst checking the overall rates of those who received community resolution and comparing it those who did not is a good starting point, it is unlikely to capture the unbiased effect. The decision to receive community resolution for particular offender can be influenced by many factors such as his/her age, offence committed, employment status and more. These factors could also influence offender's future decision whether to reoffend or not. Therefore, by simply comparing reoffending rates for those who received community resolution and ones who did not, we would absorb the result of all other factors influencing his/her decision to commit another offence and not a pure effect of receiving community resolution. In order to overcome this issue usually a randomised experimental design would be a preferred way – one group would be randomly assigned to the community resolution and another one to the alternative police outcome. Then we could simply compare the outcome (reoffending rate) for both groups and see if there is any significant difference. However, in reality this kind of experimental design is difficult to implement especially in crime studies as decisions on sentences issued by the justice system are not done on random basis. As an alternative, instead of exercising physical control over the treatment conditions as in the case in the randomized environment, we can exercise statistical control over the conditions by selecting a group that has similar characteristics to the treatment group (Apel and Sweeten, 2010).

This can be achieved by utilising a Propensity Score Matching method which allows us to form a control group which is statistically similar to the group which received the treatment which in our case is community resolution. To understand the propensity score matching, it is important to mention the analysis known as *potential outcomes* (Rubin, 1974). According to this framework, the causal effect of a binary treatment is the difference between an individual's value of the response variable when he/she received the treatment and that same individual's value of the response variable when he/she has not received the treatment (Apel and Sweeten, 2010). Then, the same individual experiences a response under two simultaneous conditions. The main problem of causal inference is that for each individual you can only observe one of the two potential outcomes at any given time. Therefore, it is impossible to make a direct estimation of the causal effect of treatment received.

As explained by Apel and Sweeten (2010) the goal of treatment effect estimation is to input hypothetical values for these missing counterfactuals which are the potential outcome if no treatment is received in the treated sample the potential outcome of the treatment in untreated sample (formalised approach based on Apel and Sweeten (2010) is shown in Appendix C.1). They explain that the underlying issue for estimation of the causal effect of treatments is ensuring that treated individuals are statistically equivalent to untreated individuals on all background factors that are relevant for estimating the causal effect of interest. If that is achieved then the treatment is considered to be exogenous, meaning that it is independent of the potential outcomes. The problem arises when treatment is endogenous and has an effect on the potential outcomes. In the community resolution and reoffending example, individuals who are willing to apologise or pay for the damages they have caused to the victims might have a variety of other characteristics that are correlated with a lower chance of reoffending such as better income or employment prospects, or be different in ways that are more difficult to observe and measure such as life ambitions, desire to make amends with others, how important family's and friends' opinions are to them or orientation to family life. Therefore, the main goal of causal treatment effect estimation is to deal with endogeneity as far as possible. As mentioned earlier, randomization of treatment is not always possible to achieve, therefore researchers strive to achieve statistical control over treatment in a way that approximates to conditions of randomization. It can be done by choosing a counterfactual group of untreated individuals who closely resemble the individuals who received the treatment as measured by a number of potential confounding variables. Propensity score matching allows us to select a subsample of individuals who received and have not received a treatment that are observationally similar so that valid treatment effect estimated can be calculated. Rooted in the work of Rosenbaum and Rubin (1983, 1985) and can be defined as the conditional probability of assignment to a particular treatment given a vector of observed covariates. Propensity score matching differs from standard regression by not relying on a linear functional form to estimate treatment effects and it highlights the issue of common support.

Since we believe that police were not issuing community resolutions on a random basis, in this analysis we use Propensity score matching method for constructing a comparison group and then we estimate the Average Treatment Effect which shows the effect of community resolution on reoffending rates.

4.4 Data

This analysis uses an individual-level dataset compiled by Norfolk and Suffolk police during the years 2010 to 2014. It includes information on offender characteristics such as gender, age at first offence, ethnicity, employment status, nationality. It also includes details about the crime they have committed, what was the police outcome and, if they reoffended, when it happened. There are 18767 offences recorded in the data set compiled by police with all offences listed separately with each offender being given a unique code. We recategorised data to be listed by each offender and not the offence. If we kept the data for the offences which were multiples for the reoffence, we would have skewed the data and made the effect of the treatment larger as the same offender who committed more than one offence would have been matched with a counterfactual multiple times. Therefore, our new dataset consists of 7679 observations (of offenders), 631 of whom received community resolution as the police outcome.

Reoffending

The outcome variable in this analysis is reoffending. It is measured by any arrest for a crime occurring after the first offence. The reoffending outcome is a binary variable coded 0 for those who were not re-arrested and 1 for those who were re-arrested. Also, we calculated the difference in days between the first offence and the first reoffence for those offenders who committed more than one offence. Then we categorised them as "Reoffended within 30 days", "Reoffended within 90 days" and "Reoffended within 180 days"[17] and all these variables were binary with offenders with no reoffences or who reoffended after more than 30, 90 or 180 days respectively coded 0 and those who committed another offence within those given days coded 1.

Community Resolution (Treatment)

In this analysis treatment is community resolution as a police outcome received by offenders. It is coded as a binary variable, 0 for those with no community resolution as a police outcome, and 1 for those with community resolution as a police outcome.

Covariates[18]

Gender

[17] It is a usual practice to measure reoffence with a certain follow up period, by the definition "A reoffence is defined as any offence committed in a three month follow-up period that resulted in a court conviction or caution in the three month follow up with a further three month waiting period" Ministry of Justice, 2015.
[18] Appendix C.2 illustrates descriptive statistics of four covariates listed below

Gender of an offender as identified in the police records. It is coded as a binary variable, 0 for male offenders, and 1 for female offenders.

Age

Age of an offender at first offence as identified in the police records.

Ethnicity

Ethnicity of an offender where identified in the police records. It is coded as a binary variable, 0 for white offenders, and 1 for non-white offenders.

Employment Status

Employment status of an offender where identified in the police records. It is coded as a binary variable, 0 for unemployed offenders, and 1 for employed.

Current Crime

Crime committed was also identified in the police records for each offence. Since police had no set categories of crime descriptions, we utilised word search commands and categorised most crimes into 4 main categories which came across as the most used. We then created binary variables if offence description contained the word assault, theft, criminal damage or harassment.

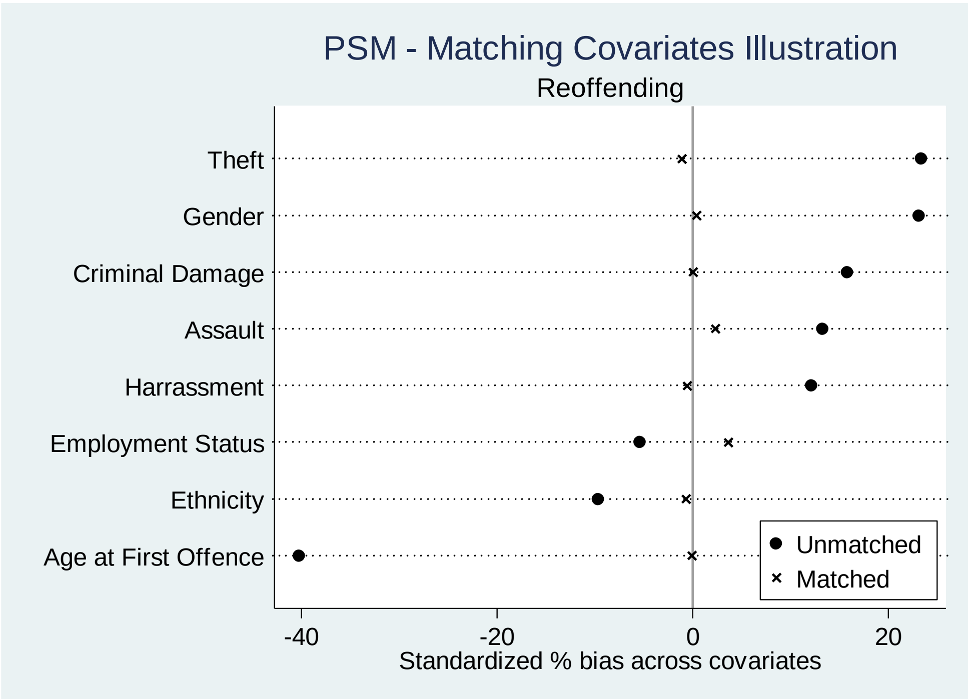
We started by matching the treatment and control group samples and then checking if matching made differences between them insignificant. Table 12 below shows the descriptive statistics of the matched and unmatched samples.

Table 12 Descriptive Statistics of Matched and Unmatched Samples

Variable	Description	Mean						t-test	
		Unmatched		Matched					
		Treated	Control	Treated	Control	%bias reduction	%bias	t	p>|t|
Reoffending	Police record of one more arrest after committing first offence (0 = no, 1 = yes)								
Treatment	Receiving Community Resolution as police outcome (0 = no, 1 = yes)								
Sociodemographic									
Gender	0 = Male, 1 = Female	0.25	0.15	0.25	0.24	98.2	0.4	0.07	0.95
Ethnicity	0 = White, 1 = Non-White	0.05	0.07	0.05	0.05	92.8	-0.7	-0.13	0.89
Age at the first offence	Age at admission	24.3	29.4	24.3	24.3	99.7	-0.1	-0.02	0.99
Employment	0 = unemployed, 1 = employed	0.59	0.62	0.59	0.57	32.8	3.6	0.63	0.53
Current crime									
Assault	0 = no, 1 = yes	0.26	0.2	0.26	0.25	82.7	2.3	0.39	0.7
Criminal Damage	0 = no, 1 = yes	0.13	0.08	0.13	0.13	100	0	0	1
Theft	0 = no, 1 = yes	0.29	0.19	0.29	0.3	95.1	-1.1	-0.19	0.85
Harassment	0 = no, 1 = yes	0.09	0.06	0.09	0.09	95	-0.6	-0.1	0.92

We can see from the table results that matching leads to both groups (treatment and control) having similar characteristics. Means of matched and unmatched groups are presented on the left of the table and we can see how close the characteristics between treatment and control groups after the matching are. On the right of the Table 12 the standardized bias after matching satisfies the condition to be under 5%. Also, t-tests demonstrate that all the differences after matching were not significant, or in other words, these groups were balanced in their propensity to receive community resolution. Figure 6 below illustrates the matching.

Figure 6 PSM - Matching Covariates Illustration



4.5 PSM Results

4.5.1 Main Results

After successfully matching treatment and control groups, we are using a one-to-one nearest-neighbour matching method[19] with no replacement to calculate the average treatment effect of community resolution as a police outcome on reoffending rates. There were 620 matched pairs found and Table 14 below shows our findings:

Table 13: Average Treatment Effect: Propensity Score Matching (Main Results)

Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffending						
	Before Matching	0.42	0.49	-0.077	0.02	-3.6
	After Matching	0.42	0.52	-0.108	0.03	-3.83

Before matching, the treated group reoffended at the rate of 42% and the control group at 49%. After matching, the control group had a reoffending rate of 52%. Therefore, after matching we can observe the difference in reoffending rates between treated and control groups is -10.8% and is statistically significant. This finding shows that community resolution has a negative (reducing) effect on the reoffending rates.

[19] There are alternative matching criteria, but we have chosen one to one nearest neighbour matching to get the closest matches possible to our treatment group. In the large sample all matching criteria should provide very similar results and they all choose the best possible matches for the sample.

On average offenders who committed another offence took 190 days between their index offence and their next offence and we are interested in seeing if community resolution had any effect on how quickly offenders reoffended.

Table 14 Average Treatment Effect: Propensity Score Matching (Main Results by Reoffending Days)

Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffence within 30 days						
	Before Matching	0.003	0.026	-0.023	0.006	-3.55
	After Matching	0.003	0.031	-0.023	0.007	-3.34
Reoffence within 90 days						
	Before Matching	0.04	0.07	-0.027	0.01	-2.56
	After Matching	0.04	0.07	-0.029	0.01	-2.22
Reoffence within 180 days						
	Before Matching	0.11	0.16	-0.052	0.02	-3.4
	After Matching	0.11	0.18	-0.069	0.02	-3.51
Reoffence within 12 months						
	Before Matching	0.35	0.43	-0.082	0.02	-3.9
	After Matching	0.35	0.45	-0.105	0.03	-3.79

Table 15 shows the average treatment of community resolution on four different reoffending intervals before and after matching. The first set of rows show the reoffending rate within 30 days of index offence (which is the first offence recorded by the police for each offender in our data set). Before and after matching the difference between treated and control groups was -2% and it is statistically significant (two-tail t test at 0.01 level). The results of 90 days recidivism intervals are similar. The differences in the reoffending rate are -2.7% before matching and -2.9% after matching. They are both statistically significant. The next rows in the table show the reoffending rates within 180 days of index offence. Before matching, the average recidivism rate for those who did not receive community resolution as police outcome was 16% while for those who received it was 11%. After matching, the results remained very similar and both were statistically significant. In 12 months the overall reoffending rate for those who received the treatment before matching was 35% and for those who did not was 43%. After matching, those who received the treatment reoffended at the rate of 35% while those who did not receive the treatment reoffended the rate of 45% which shows a difference of 10.5% if CR is received. Both results were statistically significant.

Furthermore, we want to establish whether similar results hold across different offender profiles, thus we use the same method of matching on various subgroups corresponding to different offender profiles within our dataset.

4.5.1.1 Male Only Sample

6375 offenders (83%) in our data set were identified as males. Using the same method of matching we obtained the average treatment effect for the male only sample (Table with descriptive statistics is available in Appendix C.3):

Table 15 Average Treatment Effect: Propensity Score Matching (Male Only Sample Results)						
Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffending						
	Before Matching	0.4	0.49	-0.09	0.02	-3.67
	After Matching	0.4	0.53	-0.126	0.03	-3.89

Table 16 above shows the average treatment effects of CR as police outcome on reoffending before and after matching on male sample only. Before matching, the treated group reoffended at the rate of 40% and the control group at 49%. After matching, the control group had a reoffending rate of 53%. The results are consistent with our main findings and show that recidivism rates are around 12.6% lower after CR is received as a police outcome.

Table 16: Average Treatment Effect: Propensity Score Matching (Male Only Sample Results by Reoffending Days)						
Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffence within 30 days						
	Before Matching	0.002	0.025	-0.023	0.01	-3.12
	After Matching	0.002	0.017	-0.015	0.01	-2.35
Reoffence within 90 days						
	Before Matching	0.041	0.067	-0.026	0.01	-2.17
	After Matching	0.041	0.062	-0.021	0.01	-1.48
Reoffence within 180 days						
	Before Matching	0.096	0.16	-0.062	0.02	-3.54
	After Matching	0.096	0.16	-0.068	0.02	-3.12
Reoffence within 12 months						
	Before Matching	0.34	0.43	-0.091	0.02	-3.78
	After Matching	0.34	0.45	-0.115	0.03	-3.63

Table 17 above breaks down recidivism into four time intervals. Results are mostly significant and indicate a drop in reoffending after CR is received as a police outcome.

4.5.1.2 Sample with Employed Only

3154 offenders (41%) in our sample were identified as employed. Using the same method of matching, we obtained the average treatment effect for the employed only sample (Table with descriptive statistics is available in Appendix C.4):

Table 17: Average Treatment Effect: Propensity Score Matching (Employed Only Sample Results)

Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffending						
	Before Matching	0.36	0.43	-0.073	0.03	-2.68
	After Matching	0.36	0.44	-0.076	0.04	-2.12

In the employed only sample, treated offenders reoffended less when compared to a pulled sample (main findings). Before matching, the treated group reoffended at 36% and control group at 43%. After matching control group had a reoffending rate of 44%. Before matching, the difference in reoffending rates between treated and control groups is 7.3% and after matching it is 7.6%. Both are statistically significant.

Table 18 Average Treatment Effect: Propensity Score Matching (Employed Only Sample Results by Reoffending Days)						
Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffence within 30 days						
	Before Matching	0.005	0.025	-0.019	0.01	-2.34
	After Matching	0.005	0.022	-0.016	0.01	-1.91
Reoffence within 90 days						
	Before Matching	0.038	0.067	-0.029	0.01	-2.16
	After Matching	0.038	0.054	-0.16	0.02	-1.05
Reoffence within 180 days						
	Before Matching	0.1	0.145	-0.044	0.02	-2.3
	After Matching	0.1	0.139	-0.038	0.02	-1.59
Reoffence within 12 months						
	Before Matching	0.313	0.392	-0.078	0.03	-2.9
	After Matching	0.313	0.395	-0.082	0.04	-2.32

Results for reoffending at different time intervals are shown in the Table 19 above. They show that the same as with our main findings, CR has a negative effect on recidivism on employed only sample.

4.5.1.3 Sample with Unemployed Only

1960 offenders (26%) in our sample were identified as unemployed. The results for the average treatment effect for the unemployed sample only are presented in Table 19 below (Table with descriptive statistics is available in Appendix C.5):

Table 19: Average Treatment Effect: Propensity Score Matching (Unemployed Only Sample Results)						
Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffending						
	Before Matching	0.5	0.59	-0.092	0.03	-2.78
	After Matching	0.5	0.63	-0.134	0.04	-3.07

Treated groups before and after matching had an overall rate of reoffending of 50%. Control group before matching had a reoffending rate of 59% and after matching it was 63%. These numbers are higher than for main findings and employed only sample suggesting that recidivism is higher amongst the unemployed offenders. The difference in reoffending between two groups before matching was 9.2% and after matching it was 13.4%. Both were statistically significant. These findings show that community resolution can be an effective way to reduce reoffending.

Table 20: Average Treatment Effect: Propensity Score Matching (Unemployed Only Sample Results by Reoffending Days)						
Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffence within 30 days						
	Before Matching	0	0.029	-0.029	0.01	-2.74
	After Matching	0	0.028	-0.028	0.01	-2.68
Reoffence within 90 days						
	Before Matching	0.047	0.072	-0.024	0.02	-1.43
	After Matching	0.047	0.079	-0.031	0.02	-1.46
Reoffence within 180 days						
	Before Matching	0.12	0.19	-0.067	0.03	-2.62
	After Matching	0.12	0.23	-0.111	0.03	-3.31
Reoffence within 12 months						
	Before Matching	0.4	0.49	-0.095	0.03	-2.83
	After Matching	0.4	0.53	-0.126	0.04	-2.87

Table 21 above contains results on reoffending at different time intervals. No unemployed offenders who received CR as a police outcome reoffended in the first 30 days. Overall, these findings are consistent with our results for the whole sample and most are statistically significant.

4.5.1.4 Sample with Juvenile Offenders Only

In our data set 1317 offenders (17%) were aged below 18. Descriptive statistics of unmatched and matched samples is available in Appendix C.6. Table 21 below presents the findings for the average treatment effect for the sample of juvenile only:

Table 21: Average Treatment Effect: Propensity Score Matching (Juvenile Only Sample Results)

Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffending						
	Before Matching	0.43	0.51	-0.083	0.04	-2.27
	After Matching	0.43	0.48	-0.049	0.04	-1.13

Before and after matching juvenile offenders reoffended at 43% rate. Before matching, control group reoffended at 51% rate and after matching at 49% rate. The difference before matching was 8% and statistically significant and after matching it become 6% and was statistically insignificant.

Table 22 Average Treatment Effect: Propensity Score Matching (Juvenile Only Sample Results by Reoffending Days)						
Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffence within 30 days						
	Before Matching	0.004	0.023	-0.02	0.01	-2.04
	After Matching	0.004	0.019	-0.015	0.01	-1.64
Reoffence within 90 days						
	Before Matching	0.026	0.057	-0.03	0.02	-1.95
	After Matching	0.026	0.049	-0.022	0.02	-1.37
Reoffence within 180 days						
	Before Matching	0.097	0.136	-0.039	0.02	-1.61
	After Matching	0.097	0.131	-0.034	0.03	-1.22
Reoffence within 12 months						
	Before Matching	0.36	0.423	-0.063	0.04	-1.75
	After Matching	0.36	0.397	-0.037	0.04	-0.89

Table 23 above contains results on reoffending at different time intervals. No juvenile offenders who received CR as a police outcome reoffended in the first 30 days. Overall, findings are consistent with our main results and show there is a reduction in recidivism after CR is received as a police outcome, however, the differences are lower than – overall the difference in reoffending rates after matching after 12 months is around 10% whilst for juveniles it is around 5%.

4.5.1.5 Sample with Adult Offenders Only

6362 offenders (83%) in our sample were identified as 18 or over. The results for the average treatment effect for the adult only sample are presented in the Table 23 below (Table with descriptive statistics is available in Appendix C.7):

Table 23: Average Treatment Effect: Propensity Score Matching (Adult Only Sample Results)						
Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffending						
	Before Matching	0.41	0.49	-0.084	0.03	-3.05
	After Matching	0.41	0.59	-0.187	0.04	-5.05

Before and after matching treatment group reoffended at 41% rate. Control group before matching were reoffending at the 49% rate and after matching at 59% rate. The difference after receiving CR as a police outcome before matching was 8.4% and after matching 18.7% showing that CR can have a large impact on recidivism rates on adult offenders. Both results were statistically significant.

Table 24: Average Treatment Effect: Propensity Score Matching (Adult Only Sample Results by Reoffending Days)						
Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffence within 30 days						
	Before Matching	0.003	0.027	-0.024	0.01	-2.77
	After Matching	0.003	0.048	-0.045	0.01	-3.85
Reoffence within 90 days						
	Before Matching	0.054	0.071	-0.017	0.01	-1.22
	After Matching	0.054	0.076	-0.023	0.02	-1.22
Reoffence within 180 days						
	Before Matching	0.12	0.16	-0.048	0.02	-2.37
	After Matching	0.12	0.2	-0.08	0.03	-3.2
Reoffence within 12 months						
	Before Matching	0.34	0.43	-0.1	0.03	-3.36
	After Matching	0.34	0.51	-0.17	0.04	-4.63

Table 25 above contains results on reoffending at different time intervals. Findings are consistent with our main results and show there is a reduction in recidivism after CR is received as a police outcome and most are statistically significant.

We now disaggregate by offence type and redo the analysis for each category

4.5.1.6 Sample with Assault Offences Only

1652 offences (22%) in our sample were identified as assault with around 10% of them getting a CR as a police outcome. The results for the average treatment effect for the assault offences only sample are presented in the Table 25 below (Table with descriptive statistics is available in Appendix C.8):

Table 25: Average Treatment Effect: Propensity Score Matching (Assault Only Results)

Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffending						
	Before Matching	0.37	0.44	-0.075	0.04	-1.78
	After Matching	0.37	0.43	-0.062	0.05	-1.14

Before and after matching the group which received the Community Resolution as a police outcome reoffender at 37% rate. Control group reoffended at 44% rate before matching and at 43% rate after matching. Both results indicated that community resolution would lead to lower reoffending rates, however, results were not statistically significant.

Table 26: Average Treatment Effect: Propensity Score Matching (Assault Only Results by Reoffending Days)						
Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffence within 30 days						
	Before Matching	0	0.02	-0.024	0.01	-2
	After Matching	0	0.02	-0.025	0.01	-2.02
Reoffence within 90 days						
	Before Matching	0.03	0.07	-0.035	0.02	-1.71
	After Matching	0.03	0.07	-0.037	0.02	-1.54
Reoffence within 180 days						
	Before Matching	0.13	0.16	-0.031	0.03	-1.01
	After Matching	0.13	0.18	-0.05	0.04	-1.23
Reoffence within 12 months						
	Before Matching	0.3	0.41	-0.11	0.04	-2.65
	After Matching	0.3	0.4	-0.106	0.05	-1.99

Table 27 above shows results for reoffending at different time intervals. Results are consistent with our main findings and show that there is an 11% decrease in reoffending rates within 12 months after CR is received as a police outcome. It is also statistically significant.

4.5.1.7 Sample with Theft Offences Only

1664 offences (22%) in our sample were identified as assault with around 11% of them getting a CR as a police outcome. The results for the average treatment effect for the theft offences only sample are presented in the Table 28 below (Table with descriptive statistics is available in Appendix C.9):

Table 27: Average Treatment Effects: Propensity Score Matching (Theft Only Results)

Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffending						
	Before Matching	0.48	0.6	-0.127	0.04	-3.14
	After Matching	0.48	0.63	-0.156	0.05	-3.00

Before and after matching offenders who got identified with theft as the offence type by the police and received CR as a police outcome reoffended at 48% rate. Control group before matching reoffender at 60% rate and after matching at 63%. It indicates that before matching there was a difference of 12.7% in reoffending rates and 15.6% after matching. Both results are statistically significant.

Table 28: Average Treatment Effect: Propensity Score Matching (Theft Only Results by Reoffending Days)

Variable	Sample	Treated	Control	Difference	S.E.	T-stats
Reoffence within 30 days						
	Before Matching	0	0.03	-0.029	0.01	-2.33
	After Matching	0	0.03	-0.033	0.01	-2.48
Reoffence within 90 days						
	Before Matching	0.04	0.08	-0.039	0.02	-1.84
	After Matching	0.04	0.06	-0.022	0.02	-0.97
Reoffence within 180 days						
	Before Matching	0.11	0.18	-0.075	0.03	-2.46
	After Matching	0.11	0.21	-0.106	0.04	-2.76

Reoffence within 12 months					
Before Matching	0.41	0.5	-0.096	0.04	-2.34
After Matching	0.41	0.52	-0.117	0.05	-2.23

Reoffending rates by different time intervals are consistent with our main findings. Reoffending within 12 months is almost 12% lower for those who received CR as a police outcome and is statistically significant.

4.6 Survival Analysis

We further analyse the impact of CR on reoffending rates by utilising a survival analysis method. Survival analysis model is usually used to analyse the survival times, i.e., the time until death, in medical studies. In criminology it is widely used (Ostermann, 2015, Kim and Clark, 2013, Cloyes et al., 2010) to analyse the time from an individual's release from prison until his or her recidivism. As explained by Chung et al (1991) survival analysis in crime studies can yield three types of results – firstly, the survival time analysis model will predict the number of individuals who will become recidivists at any length of time after release; secondly, using this form of analysis allows one to estimate the effects of observable individual characteristics on time until the reoffence takes place; finally, if one of the individual characteristics is a dummy variable indicating the attendance or non-attendance in some correctional programme (or receiving or not receiving some treatment) which is believed to have an effect on future recidivism, holding other observable characteristics constant, the survival analysis model can be used to estimate the effect of the program or treatment. This method allows us to control for the amount of at-risk time each offender had while in community. Since we are interested in when the reoffence took place, this is particularly important.

We used a proportional hazard model (Cox regression, see Cox, 1972) where samples matched using the PSM method were analysed to see how quickly the treated and control groups reoffended after receiving CR as a police outcome. This model allows us to evaluate simultaneously the effect of various factors on survival which in this chapter can be interpreted as examining how our known covariates influence the rate of reoffending at a particular point in time. This rate is known as the hazard rate. A Cox model is expressed by the hazard function *h(t)*, which can be described as the risk of reoffending[20] at time t. It can be estimated as follow:

$$h(t) = h_0(t) \times \exp(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_z x_z)$$

where h(t) is the hazard function which is determined by a set of z covariates x_1 , x_2,…, x_z , , the coefficients β measure the effect of covariates, t is the survival time (time till reoffence), the term $h_0(t)$ is called the baseline hazard which is the hazard when all covariates are equal to zero. The main

[20] Risk of reoffending is a hazard function which is a way to model data distribution in survival analysis. In my analysis it is used to model an offender's chance of reoffence as a function of the number of days since their first offence.

assumption in the Cox model is the proportional hazards assumption. It implies that the hazard ratio (the ratio of the hazard function to the baseline hazard) for any two individuals is constant over time. A hazard ratio estimated by a Cox proportional hazards model is interpreted as a relative risk which implies that hazard ratios higher than 1 show increase in the hazard and hazard ratios lower than 1 show decrease in the hazard.

4.6.2 Survival Analysis Results

The matched sample is used for a Cox regression and results are presented in Table 28. The model includes a treatment variable, indicating whether or not an offender received CR as a police outcome and all other covariates used in the PSM analysis. We first tested whether the data satisfy the proportional hazards assumption and found that the model was suitable and covariates do not have different effects at different points in time. Our findings are consistent with our earlier analysis and show that receiving CR decreased the risk of reoffending within 12 months from the first offence by nearly 30% while holding other covariates constant[21]. For those who have not reoffended after 12 months of their first offence, their survival rate is about 68% for those who received CR and 57% for those who did not (Fig 8). Besides the treatment (CR) variable, age at the first offence, employment and theft variables are also significant in the Cox regression equation. The coefficient

[21] 1 – 0.71 = 0.29

on age is 0.99 which shows that an increase of one year of age, lowers the risk of reoffending to by 1%. This finding is consistent with our results in the PSM section where we found higher reoffending rates for juvenile offenders and smaller average treatment effect of CR when compared to older adult offenders. Being employed also reduces the risk of reoffending by about 26% which is again consistent with results from the PSM section. Finally, being caught for theft (while holding other covariates constant) increased the risk of reoffending by 26%. It is also consistent with the PSM findings where theft only sample had a higher reoffending rate when compared to the main results from the pooled sample.

Table 29: Cox Regression Model Results		
	Haz. Ratio	Std. Error
Community Resolution (0 = No, 1 = Yes)	**0.71*** **	0.002
Age at the first offence	**0.99***	0.03
Gender (0 = Male, 1 = Female)	1.01	0.06
Ethnicity (0 = White, 1 = Non-White)	1.04	0.09
Employment (0 = Unemployed, 1 = Employed)	**0.74*** **	0.03
Assault ((0 = No, 1 = Yes)	1.03	0.06
Criminal Damage (0 = No, 1 = Yes)	1.14	0.09
Theft (0 = No, 1 = Yes)	**1.26*** **	0.07
Possession (0 = No, 1 = Yes)	1.02	0.08
Note: * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$		LR chi^2 (9) = 88.94 ($P<0.001$)

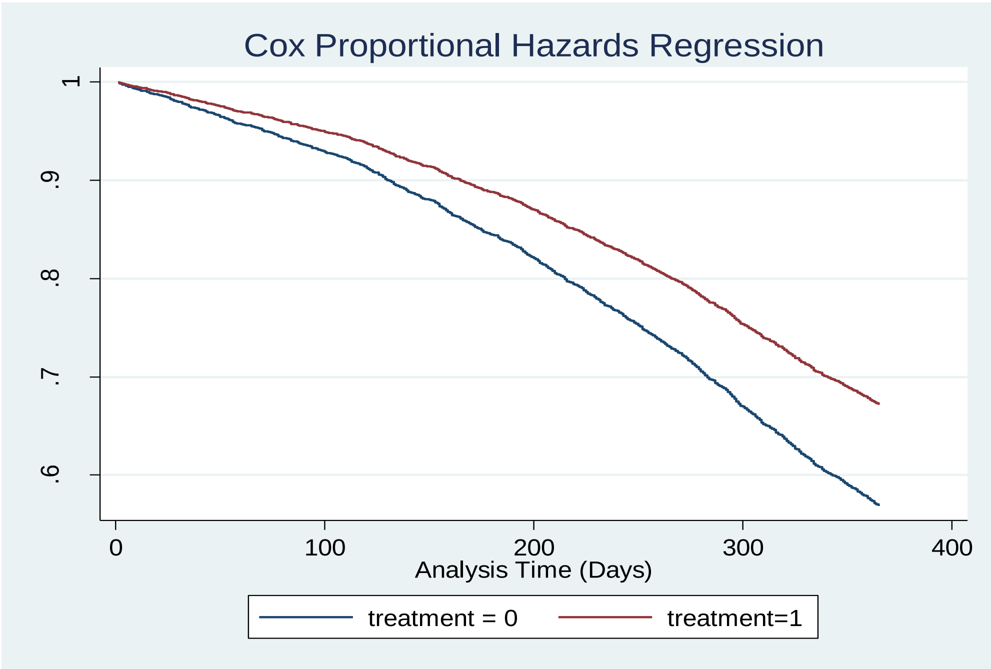


Figure 7: Cox Proportional Hazards Regression

In summary, we find that Community Resolution can effectively reduce reoffending rates. Both modelling approaches used in this chapter show consistently positive results i.e. CR reduces both reoffending rates and time to reoffend. Thus, our results suggest that when an offender received CR as a police outcome compared to a normal criminal justice procedure, he or she would be significantly less likely to reoffend at the later stage. Also, their time to reoffend is longer than those who received a non CR police outcome.

Overall, using both approaches – PSM and Survival Analysis – we find that Community Resolution has a reducing effect on reoffending. The result is consistent and robust when tested on various subsamples. Also, from the survival analysis we know that offenders' time to reoffend is longer for those who received a CR as police outcome. When comparing employed and unemployed samples, we find that offenders who were employed and received CR reoffended at 36% whilst those who were unemployed and received CR reoffended at 50%. However, the average treatment effect for unemployed sample was over 13% while for employed sample it was just below 8%. Furthermore, we find that the average treatment effect for juvenile offenders was smaller at just over 4% (when compared to the main results) and statistically insignificant while for adult offenders it was almost 19% and statistically significant. This finding suggest that CR works better on adult offenders and is in line with what rational theory posits, where an individual would choose activities in the illegal sector if their reward is higher than in the legal sector. On average young people earn less than their older counterparts which would explain their higher reoffending rates and the smaller average treatment effect of CR.

4.7 Conclusion

Community Resolutions were introduced in 2009 and provide police with a timely and effective way to deal with lower level crime and anti-social incidents reported. The goal of the analysis in this chapter is to use a unique, individual level dataset for Norfolk and Suffolk Police Force Areas for low level offenders to examine the effectiveness of Community Resolution on recidivism by employing a Propensity Score Matching and Survival Analysis. Different time intervals for reoffending for outcome variable were used and our results show that Community Resolution can have a reducing impact on further offences committed by those offenders who received it. This holds when we split offenders to groups by their characteristics to check for heterogeneous effects with most groups showing lower recidivism rates after CR. We found that adults and employed offenders had lower reoffending rates when compared to unemployed and juvenile offenders and we also found that adult offenders had the largest average treatment effect of almost 19% after receiving CR as a police outcome. Also, our results from using Survival Analysis found offenders' survival rate was about 68% for those who received CR and 57% for those offenders who did not. Or in other words, offenders who received CR survived without reoffending for longer than those who did not receive it. Overall, our findings suggest that CR can reduce reoffending rates for most types of offenders and for most type of offences that are eligible for such a resolution.

5. Conclusion

The three chapters of this thesis analyse three research questions which all aim to understand what deters crime and 'what works where'.

In the first chapter, we try to contribute to an existing literature by analysing how the effectiveness of the justice system affects crime rates by analysing the impact of the swiftness of the justice system in addition to severity of punishment and certainty of detection. We find that detection plays an important role in reducing crime and that severity of sentencing has a more ambiguous effect and varies across crime types. We also find that swiftness of the justice system might have a different effect than existing theoretical thinking. For some crime types, there is no net impact and for others categories, less crimes could be committed whilst waiting for judicial proceedings if there is higher level of monitoring and, therefore, higher detection rate, whilst waiting.

In the second chapter, we explore how effective non-custodial sentences can be in reducing crime rates. We find that for certain crime types alternatives to custody can be either superior or equivalent to a prison sentence in effectiveness. Prison sentences generally are much more costly than the alternatives and our results suggests that there is scope to combat crime through the criminal justice system in a more humane as well as cost effective way.

In the third chapter, we use individual level data on low level offenders in Norfolk and Suffolk Police Force Areas and examine the effectiveness of a particular type of alternative to custody, viz. Community Resolution on reoffending rates. We use different time intervals of reoffending rates as our outcome variable and our results show that Community Resolution has a reducing impact on recidivism. To our knowledge, it is the first study analysing the effectiveness of Community Resolution on recidivism outcomes.

To conclude, across all three chapters we find that crime types differ in how they respond to changes in criminal justice practices whether it is a longer wait for the trial or to the type of sentence issued. Therefore, there is no single answer in how crime rates can be reduced but there is a further need to explore differences across crimes and offenders and the impact policing and criminal justice interventions have when trying to reduce total crime and reoffending rates.

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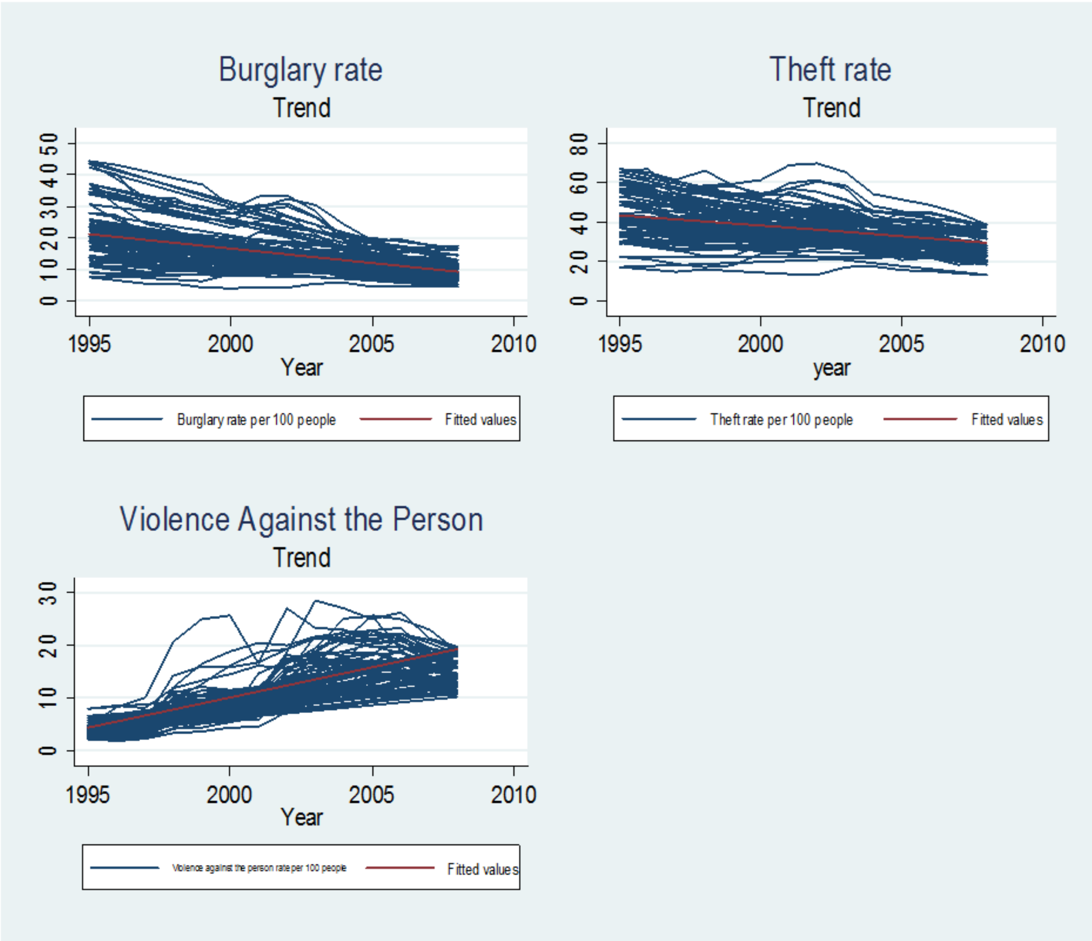
A Is Justice delayed justice denied? Exploring the impact of sanction celerity on crime

A.1 Time Trend for Burglary, Theft and Violence Against the Person Rates

Figure 8 Time Trend for Burglary, Theft and Violence Against the Person Rates, 1994 - 2008



A.2 Fixed Effects Regression Models – No Celerity and No Severity

Table 30: Fixed Effects Regression Model – No Celerity			
	Theft	Burglary	VATP
Certainty (t-1)	**-0.29*** (0.03)	**-0.17*** (0.03)	**-0.27*** (0.08)
Severity (t-1)	**-0.07*** (0.03)	**-0.19*** (0.06)	**0.29** (0.11)
Youth	-0.01 (0.19)	**-0.51*** (0.3)	-0.14 (0.6)
Population Density	-0.45 (0.38)	**-1.31** (0.54)	0.48 (0.79)
Lower Quartile Earnings Ratio	0.06 (0.17)	0.05 (0.37)	0.51 (0.37)
Time trend	Yes	Yes	Yes
Dummy	Yes	Yes	Yes
N	568	568	568
R^2 (within)	0.7	0.82	0.85
Note: dependent variable is the crime rate per 1000 people, robust standard errors are clustered at the PFA level. Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively. All variables in natural logarithm apart from the time trend.			

Table 31: Fixed Effects Regression Model – No Severity			
	Theft	Burglary	VATP
Certainty (t-1)	**-0.3*** (0.03)	**-0.18*** (0.04)	**-0.31*** (0.09)
Celerity (t-1)	0.01 (0.03)	0.06 (0.04)	**-0.24** (0.06)
Youth	-0.04 (0.2)	-0.28 (0.39)	-0.14 (0.65)
Population Density	-0.38 (0.39)	**-1.2*** (0.63)	0.63 (0.79)
Lower Quartile Earnings Ratio	0.07 (0.16)	0.77 (0.54)	0.46 (0.35)
Time trend	Yes	Yes	Yes
Dummy	Yes	Yes	Yes
N	568	337	538
R^2 (within)	0.7	0.85	0.85
Note: dependent variable is the crime rate per 1000 people, robust standard errors are clustered at the PFA level. Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively. All variables in natural logarithm apart from the time trend.			

A.3 Quadratic Model – number of days derivation

$$VATP_{rate} = 9.121 - 3.896x + 0.382x^2$$

where x is Waiting times for VATP

Then taking derivatives:

$$\frac{dVATP_{rate}}{dx} = -3.896 + 2 * (0.382)x$$

$$\frac{dVATP_{rate}}{dx} = -3.896 + 0.764x$$

Now we can plug any value of waiting times into the derivative equation and it would give us the effect of waiting times on crime rate (for violence against the person). The point at which the effect of waiting time switches from positive to negative is the turning point and the effect of waiting time at this point will be zero as it transitions from negative to positive. We calculate the waiting time (in days) at which this happens by substituting zero for the slope:

$$0 = -3.896 + 0.764x$$

$$x = \frac{3.896}{0.764} = 5.1$$

Since everything is in natural logarithms, we get that:

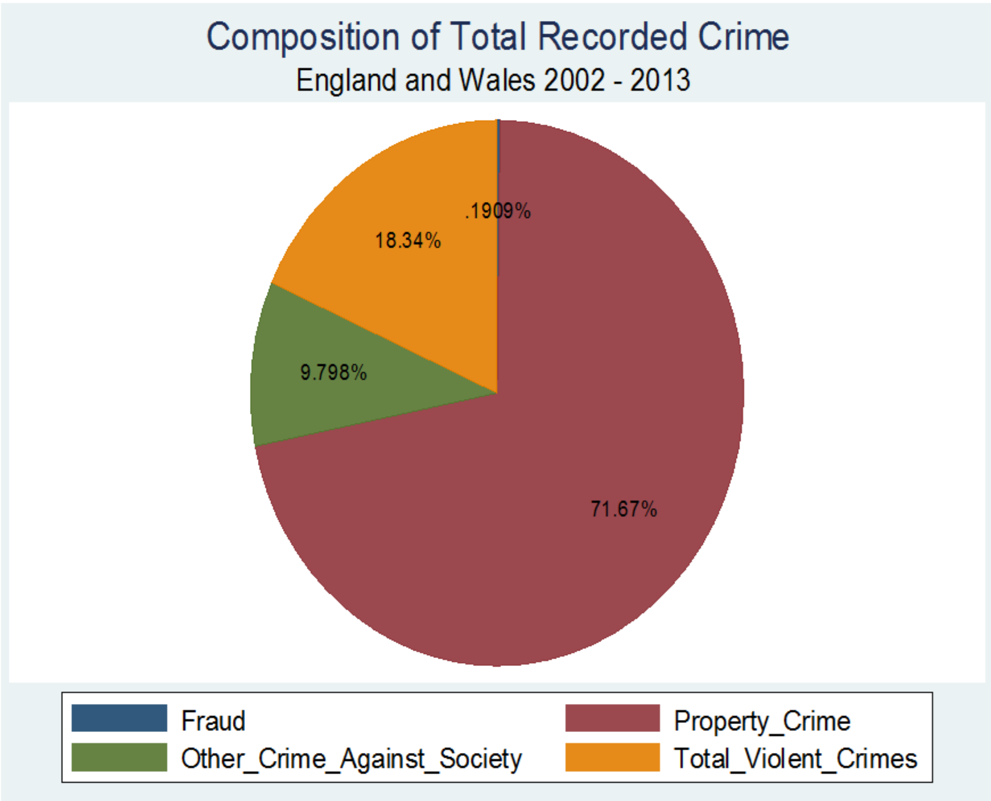
$$\ln(x) = 5.1$$

$x = e^{5.1} \sim 164$ days

B Alternatives to custody: evidence from police force areas in the United Kingdom

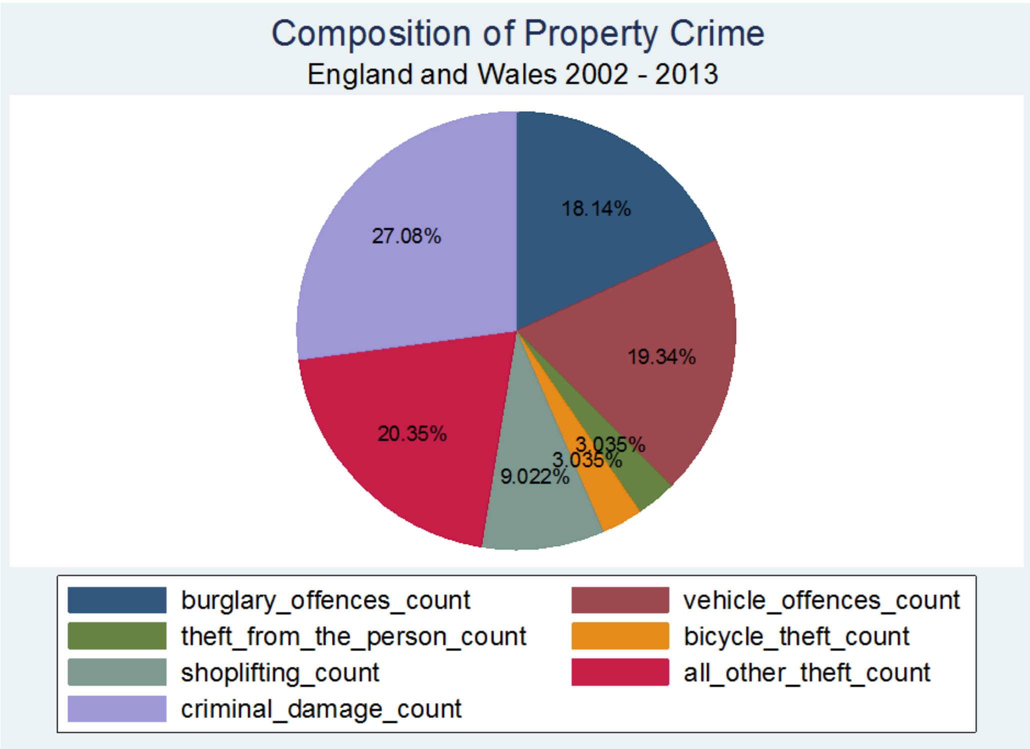
B.1 Composition of Total Recorded Crime in England and Wales 2002 - 2013

Figure 9: Composition of Total Recorded Crime in England and Wales 2002 - 2013



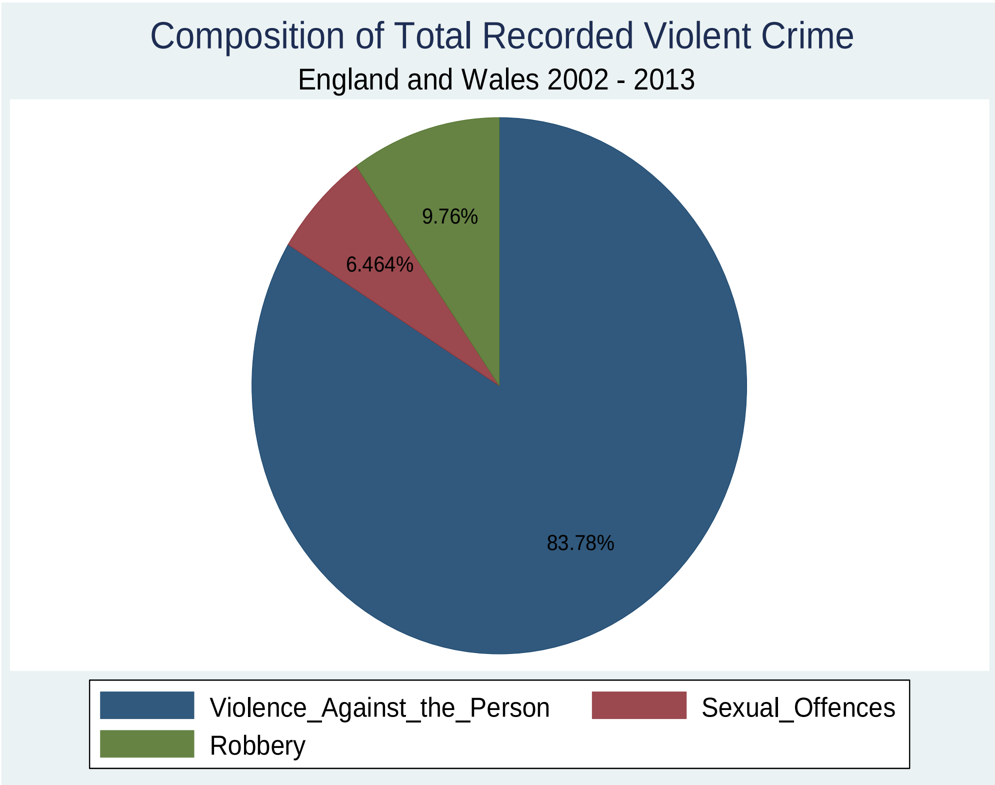
B.2 Composition of Property Crime in England and Wales, 2002 – 2013

Figure 10: Composition of Property Crime in England and Wales, 2002 – 2013



B.3 Composition of Violent Crimes in England and Wales 2002 - 2013

Figure 11: Composition of Violent Crimes in England and Wales 2002 - 2013



B.4 Conviction Rates for Violence Against the Person, Sex Offences, Robbery and Property Crime, England and Wales, 2002 – 2013

Figure 12 Conviction rates for Violence Against the Person, Sex Offences, Robbery and Property Crime, England and Wales, 2002 – 2013

B.5 Fixed Effects Regression Models Predicting Change in Crime Rates, 2002–2013

Table 32: Fixed Effects Regression Models, *level results (not in elasticity form)*	VATP	SexOff	Robbery	Property
Conviction Rate for Community Sentence (t-1)	-0.29 (0.24)	-0.01 (0.01)	**-0.03***** **(0.01)**	**-7.07***** **(1.49)**
Conviction Rate for Custody (t-1)	**-1.52***** **(0.40)**	**-0.02***** **(0.01)**	0.004 (0.003)	**-8.56**** **(3.46)**
Conviction Rate for Conditional Discharge (t-1)	-0.43 (1.3)	**-0.06**** **(0.03)**	-0.02 (0.04)	2.92 (2.15)
Conviction Rate for Fine (t-1)	0.77 (1.02)	0.02 (0.02)	0.01 (0.02)	**5.79**** **(2.82)**
Conviction Rate for Suspended Sentence (t-1)	-0.55 (0.40)	-0.03 (0.02)	0.03 (0.02)	5.74 (6.13)
Police Officers' Salaries	0.0004 (0.001)	0.0001 (0.0001)	0.00004 (0.0001)	0.003 (0.01)
Unemployment	**-0.26**** **(0.10)**	-0.01 (0.01)	**-0.06*** **(0.03)**	**-1.43***** **(0.49)**
Youth 15 - 24	-0.23 (0.26)	-0.02 (0.02)	**0.1**** **(0.04)**	**1.88**** **(0.93)**
Fixed Time Effects	Yes	Yes	Yes	Yes
Number of Observations	462	462	462	462
R^2 (within)	0.71	0.4	0.51	0.9

Note: dependent variable is the crime rate per 1000 people, robust standard errors are clustered at the PFA level (in parenthesis). Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively.

B.6 Fixed Effects Regression Models Predicting Change in Crime Rates with Adult and Juvenile Separate Specification, 2002–2013

Table 31: **Fixed Effects Regression Models, adult and juvenile separate specification*, level results (not in elasticity form)***	VATP	SexOff	Robbery	Property
Adult Conviction Rate for Community Sentence (t-1)	0.23 (0.34)	-0.01 (0.01)	**-0.03*** (0.01)	**-8.26***** (2.49)
Adult Conviction Rate for Custody (t-1)	**-1.26***** (0.39)	**-0.023***** (0.01)	**0.006*** (0.003)	**-7.53**** (3.57)
Adult Conviction Rate for Conditional Discharge (t-1)	**-3.29**** (-1.45)	**-0.06**** (0.03)	0.07 (0.06)	2.47 (2.14)
Adult Conviction Rate for Fine (t-1)	**-1.79*** (1.06)	0.02 (0.02)	0.01 (0.02)	**6.12**** (2.91)
Adult Conviction Rate for Suspended Sentence (t-1)	**-1.62***** (0.39)	-0.02 (0.02)	0.02 (0.02)	6.34 (6.07)
Juvenile Conviction Rate for Community Sentence (t-1)	-0.23 (0.56)	-0.02 (0.02)	**-0.02***** (0.009)	-1.04 (4.31)
Juvenile Conviction Rate for Custody (t-1)	**-3.14*** (1.66)	0.06 (0.08)	-0.01 (0.01)	-26.17 (24.66)
Juvenile Conviction Rate for Conditional Discharge (t-1)				-4.05 (18.76)
Juvenile Conviction Rate for Fine (t-1)				**-72.47***** (26.82)
Police Officers' Salaries	-0.0005 (0.0007)	-0.00008 (0.00007)	-0.00005 (0.001)	-0.03 (0.005)
Unemployment	**-0.26**** (0.10)	-0.013 (0.01)	**-0.06*** (0.03)	**-1.41***** (0.48)
Youth 15 - 24	-0.19 (0.28)	-0.02 (0.02)	**0.09**** (0.04)	**1.55*** (0.77)
Fixed Time Effects	Yes	Yes	Yes	Yes
Number of Observations	462	462	462	504
R^2 (within)	0.74	0.4	0.51	0.9

Note: dependent variable is the crime rate per 1000 people, robust standard errors are clustered at the PFA level (in parenthesis). Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively.

B.7 Robustness section: Fixed Effects Regression Models Predicting Change in Crime Rates with Recession Interaction Dummies, 2002–2013

Table 33: Fixed effects regression models predicting change in crime rates with recession interaction dummies	VATP	SexOff	Robb	Property
Conviction Rate for Community Sentence (t-1)	0.06 (0.45)	-0.06 (0.02)	**-0.08*** (0.01)	**-0.22***** (2.66)
Conviction Rate for Custody (t-1)	**-0.33***** (0.33)	**-0.12**** (0.01)	**-0.39***** (0.01)	-1.57 (3.30)
Conviction Rate for Conditional Discharge (t-1)	-0.03 (1.26)	-0.01 (0.03)	-0.001 (0.09)	-0.68 (3.49)
Conviction Rate for Fine (t-1)	-0.003 (1.43)	**0.01*** (0.02)	0.001 (0.20)	-0.04 (3.83)
Conviction Rate for Suspended Sentence (t-1)	**-0.1***** (0.38)	**-0.09***** (0.04)	0.01 (0.04)	**-0.07***** (4.57)
Police Officers' Salaries	0.02 (0.001)	0.03 (0.0001)	0.03 (0.0001)	0.02 (0.01)
Unemployment	0.09 (0.12)	**-0.18**** (0.01)	0.33 (0.04)	0.002 (0.51)
Youth (15 – 24)	0.09 (0.09)	-0.53 (0.03)	0.58 (0.03)	**0.4*** (0.91)
Recession Dummy (> 2007)	**6.06***** (1.86)	**0.36**** (0.17)	**0.65*** (0.39)	**30.16***** (10.90)
Conviction Rate for Community Sentence (t-1)*recession	**-0.06**** (0.35)	0.003 (0.02)	-0.0002 (0.01)	0.02 (2.68)
Conviction Rate for Custody (t-1)*recession	**0.11**** (0.57)	0.04 (0.01)	**0.25***** (0.01)	-0.06 (3.45)
Conviction Rate for Conditional Discharge (t-1)*recession	**0.03**** (1.37)	-0.003 (0.06)	-0.0004 (0.10)	0.02 (3.45)
Conviction Rate for Fine (t-1)*recession	0.003 (1.65)	-0.01 (0.03)	-0.001 (0.20)	**0.06**** (4.15)
Conviction Rate for Suspended Sentence (t-1)*recession	**0.06**** (0.57)	**0.05**** (0.04)	-0.01 (0.04)	**0.1***** (6.79)
Police Officers' Salaries*recession	-0.01	-0.004	-0.01	-0.01

	(0.001)	(0.0001)	(0.0002)	(0.004)
Unemployment*recession	**-0.1***** (0.09)	0.04 (0.01)	**-0.37***** (0.03)	**-0.06**** (0.46)
Youth (15 – 24)*recession	**-0.24***** (0.15)	**-0.27**** (0.02)	-0.22 (0.04)	**-0.28***** (0.91)
Time Trend	**-0.27***** (0.06)	**0.01**** (0.005)	**-0.07***** (0.01)	**-3.46***** (0.33)
Number of Observations	462	462	462	462
R^2 (within)	0.73	0.30	0.60	0.91

Note: dependent variable is the crime rate per 1000 people, robust standard errors are clustered at the PFA level (in parenthesis). Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively.

B.8 Fixed Effects Regression Models Predicting Change in Crime Rates with Lagged Socio Economic Variables, 2002–2013

Table 34: Fixed effects regression models predicting change in crime rates with lagged socio economic variables	VATP	SexOff	Robbery	Property
Conviction Rate for Community Sentence (t-1)	-0.04 (0.23)	-0.38 (0.01)	**-0.11***** (0.01)	**-0.22***** (1.57)
Conviction Rate for Custody (t-1)	**-0.21***** (0.39)	**-0.12***** (0.01)	0.04 (0.003)	**-0.14**** (3.52)
Conviction Rate for Conditional Discharge (t-1)	-0.007 (1.30)	**-0.02**** (0.03)	0.001 (0.04)	0.04 (2.10)
Conviction Rate for Fine (t-1)	0.01 (1.00)	0.006 (0.02)	0.01 (0.02)	**0.06**** (2.75)
Conviction Rate for Suspended Sentence (t-1)	-0.55 (0.40)	-0.01 (0.02)	0.0003 (0.02)	0.02 (6.50)
Police Officers' Salaries (t-1)	0.02 (0.001)	0.03 (0.0001)	-0.03 (0.0002)	0.04 (0.01)
Unemployment (t-1)	**-0.12**** (0.10)	**-0.12**** (0.01)	**-0.46**** (0.03)	**-0.14***** (0.46)
Youth 15 – 24 (t-1)	0.04 (0.38)	-0.13 (0.03)	2.18 (0.10)	0.34 (1.24)
Fixed Time Effects	Yes	Yes	Yes	Yes
Number of Observations	462	462	462	462
R^2 (within)	0.71	0.40	0.52	0.90

Note: dependent variable is the crime rate per 1000 people, robust standard errors are clustered at the PFA level (in parenthesis). Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively.

B.9 Robustness section – Empirical Specifications

The empirical models for the cross crime effects of sentencing section are as follows:

- For the violence against the person

$$VATPRate_{i,t} = \beta_1 CommunitySentSexOff_{i,t-1} + \beta_2 CustodySexOff_{i,t-1} + \beta_3 ConditionalDischargeSexOff_{i,t-1} + \beta_4 FineSexOff_{i,t-1} + \beta_5 SuspendedSentenceSexOff_{i,t-1} + \beta_6 ommunitySentRobbery_{i,t-1} + \beta_7 CustodyRobbery_{i,t-1} + \beta_8 ConditionalDischargeRobbery_{i,t-1} + \beta_9 FineRobbery_{i,t-1} + \beta_{10} SuspendedSentenceRobbery_{i,t-1} + \beta_{11} CommunitySentProperty_{i,t-1} + \beta_{12} CustodyProperty_{i,t-1} + \beta_{13} ConditionalDischargeProperty_{i,t-1} + \beta_{14} FineProperty_{i,t-1} + \beta_{15} SuspendedSentenceProperty_{i,t-1} + \beta_{16} PoliceOfficersSalaries_{i,t} + \beta_{17} Unempl_{i,t} + \beta_{18} Youth_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t}$$

- For sex offences

$$SexOffencesRate_{i,t} = = \beta_1 CommunitySentVATP_{i,t-1} + \beta_2 CustodyVATP_{i,t-1} + \beta_3 ConditionalDischargeVATP_{i,t-1} + \beta_4 FineVATP_{i,t-1} + \beta_5 SuspendedSentenceVATP_{i,t-1} + \beta 6_1 CommunitySentRobbery_{i,t-1} + \beta_7 CustodyRobbery_{i,t-1} + \beta_8 ConditionalDischargeRobbery_{i,t-1} + \beta_9 FineRobbery_{i,t-1} + \beta_{10} SuspendedSentenceRobbery_{i,t-1} + \beta_{11} CommunitySentProperty_{i,t-1} + \beta_{12} CustodyProperty_{i,t-1} + \beta_{13} ConditionalDischargeProperty_{i,t-1} + \beta_{14} FineProperty_{i,t-1} + \beta_{15} SuspendedSentenceProperty_{i,t-1} + \beta_{16} PoliceOfficersSalaries_{i,t} + \beta_{17} Unempl_{i,t} + \beta_{18} Youth_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t}$$

- For robbery

$$RobberyRate_{i,t} = = \beta_1 CommunitySentVATP_{i,t-1} + \beta_2 CustodyVATP_{i,t-1} + \beta_3 ConditionalDischargeVATP_{i,t-1} + \beta_4 FineVATP_{i,t-1} + \beta_5 SuspendedSentenceVATP_{i,t-1} + \beta_6 CommunitySentSexOff_{i,t-1} + \beta_7 CustodySexOff_{i,t-1} + \beta_8 ConditionalDischargeSexOff_{i,t-1} + \beta_9 FineSexOff_{i,t-1} + \beta_{10} SuspendedSentenceSexOff_{i,t-1} + \beta_{11} CommunitySentProperty_{i,t-1} + \beta_{12} CustodyProperty_{i,t-1} + \beta_{13} ConditionalDischargeProperty_{i,t-1} + \beta_{14} FineProperty_{i,t-1} + \beta_{15} SuspendedSentenceProperty_{i,t-1} + \beta_{16} PoliceOfficersSalaries_{i,t} + \beta_{17} Unempl_{i,t} + \beta_{18} Youth_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t}$$

- For property crime

$$PropertyCrimeRate_{i,t} == \beta_1 CommunitySentVATP_{i,t-1} + \beta_2 CustodyVATP_{i,t-1} + \beta_3 ConditionalDischargeVATP_{i,t-1} + \beta_4 FineVATP_{i,t-1} + \beta_5 SuspendedSentenceVATP_{i,t-1} + \beta_6 CommunitySentSexOff_{i,t-1} + \beta_7 CustodySexOff_{i,t-1} + \beta 8_3 ConditionalDischargeSexOff_{i,t-1} + \beta_9 FineSexOff_{i,t-1} + \beta_{10} SuspendedSentenceSexOff_{i,t-1} + \beta_{111} CommunitySentRobbery_{i,t-1} + \beta_{12} CustodyRobbery_{i,t-1} + \beta_{13} ConditionalDischargeRobbery_{i,t-1} + \beta_{14} FineRobbery_{i,t-1} + \beta_{15} SuspendedSentenceRobbery_{i,t-1} + \beta_{16} PoliceOfficersSalaries_{i,t} + \beta_{17} Unempl_{i,t} + \beta_{18} Youth_{i,t} + \sigma_i + \mu_t + \varepsilon_{i,t}$$

B.10 Fixed Effects Regression Models Predicting Change in Crime Rates with Cross Crime Sentencing, 2002–2013

Table 35: Fixed Effects Regression Models, Cross Crime Specification	**VATP**	**Sex Offences**	**Robbery**	**Property Crime**
VATP - Community Sentence (t-1)		-0.09	-0.08	-0.01
VATP - Custody (t-1)		-0.1	-0.11	**-0.12*** **
VATP - Conditional Discharge (t-1)		0.02	0.06	0.001
VATP - Fine (t-1)		-0.01	-0.04	-0.01
VATP - Suspended Sentence (t-1)		**0.06*** **	0.09	-0.01
Sex Offences - Community Sentence (t-1)	-0.19		**-0.09***	-0.02
Sex Offences - Custody (t-1)	**-0.06***		0.01	-0.01
Sex Offences - Conditional Discharge (t-1)	-0.01		**-0.03***	-0.004
Sex Offences - Fine (t-1)	0.01		-0.01	0.001
Sex Offences - Suspended Sentence (t-1)	**-0.03*** **		0.01	**-0.02** **
Robbery - Community Sentence (t-1)	-0.01	**-0.04***		**-0.02** **
Robbery - Custody (t-1)	-0.002	0.02		-0.01
Robbery - Conditional Discharge (t-1)	-0.01	-0.01		0.0002
Robbery - Fine (t-1)	-0.003	-0.003		0.0003
Robbery - Suspended Sentence (t-1)	0.01	-0.01		**0.01***
Property Crime - Community Sentence (t-1)	-0.02	0.03	**-0.04** **	
Property Crime - Custody (t-1)	-0.02	0.07	-0.1	
Property Crime - Conditional Discharge (t-1)	-0.06	0.01	**0.27*** **	
Property Crime - Fine (t-1)	**0.07***	-0.002	**0.22** **	
Property Crime - Suspended Sentence (t-1)	0.01	**-0.1** **	-0.13	
Police Officers' Salaries	0.002	0.03	0.01	0.02
Unemployment	**-0.15** **	-0.06	**-0.27***	**-0.2*** **
Youth 15 – 24	-0.22	-0.4	**1.17** **	**0.38** **
Fixed Time Effects	Yes	Yes	Yes	Yes
Number of Observations	462	462	462	462
R^2 (within)	0.68	0.4	0.55	0.9

Note: dependent variable is the crime rate per 1000 people. Coefficients are significant at the 10%, 5% and 1% level and are marked *, **, *** respectively

C Does Community Resolution reduce reoffending?

C.1 Causal Treatment Effect Estimation

To formalise the approach to causal treatment effect estimation, Apel and Sweeten (2010) start by assuming that all individuals in the target population have information on Y_i^1 (potential outcome if treatment is received), Y_i^0(potential outcome if no treatment is received) and T_i (whether or not treatment was received usually taking the values of 0 and 1, with 0 indicating no treatment and 1 indicting treatment taking place). With this information in mind, for each individual *i,* the causal effect of treatment is Y_i^1 - Y_i^0. Then the average treatment effect (ATE) is the expected effect of treatment on a randomly selected individual from the target population and is defined as:

$$\text{ATE} = \text{E}(Y_i^1 - Y_i^0) = \text{E}(Y_i^1) - E(Y_i^0)$$

Also, it can be written as a function of the average treatment effect on the treated (ATT) and average treatment effect of untreated (ATU). ATT is the expected effect of the treatment for those individuals in the target population who received the treatment and is defined as:

$$\text{ATT} = \text{E}(Y_i^1 - Y_i^0 \,|\, T_i = 1) = E(Y_i^1 | \, T_i = 1) - E(Y_i^0 \,\big|\, T_i = 1)$$

ATU is defined as the expected effect of treatment for those individuals who did not receive a treatment and is written as:

$$\text{ATU} = \text{E}(Y_i^1 - Y_i^0 \,|\, T_i = 0) = E(Y_i^1 | \, T_i = 0) - E(Y_i^0 \,\big|\, T_i = 0)$$

Then ATE can be rewritten as a weighted average of ATT and ATU:

$$E(Y_i^1 - Y_i^0) = \Pr(T_i = 1)\ E(Y_i^1 - Y_i^0 \mid T_i = 1) + \Pr(T_i = 0)\ E(Y_i^1 - Y_i^0 \mid T_i = 0) \qquad (1)$$

Where $\Pr(T_i = 1)\ E(Y_i^1 - Y_i^0 \mid T_i = 1)$ is ATT weighted by the probability that treatment is received and $\Pr(T_i = 0)\ E(Y_i^1 - Y_i^0 \mid T_i = 0)$ is ATU weighted by the probability that treatment is not received.

The obvious problem for causal estimation in this case is that only one of the two potential outcomes is observed for all individuals. Y_i represents the observed outcome and can be defined as:

$$Y_i = \begin{cases} Y_i^1 \text{if } T_i = 1 \\ Y_i^0 if\ T_i = 0 \end{cases}$$

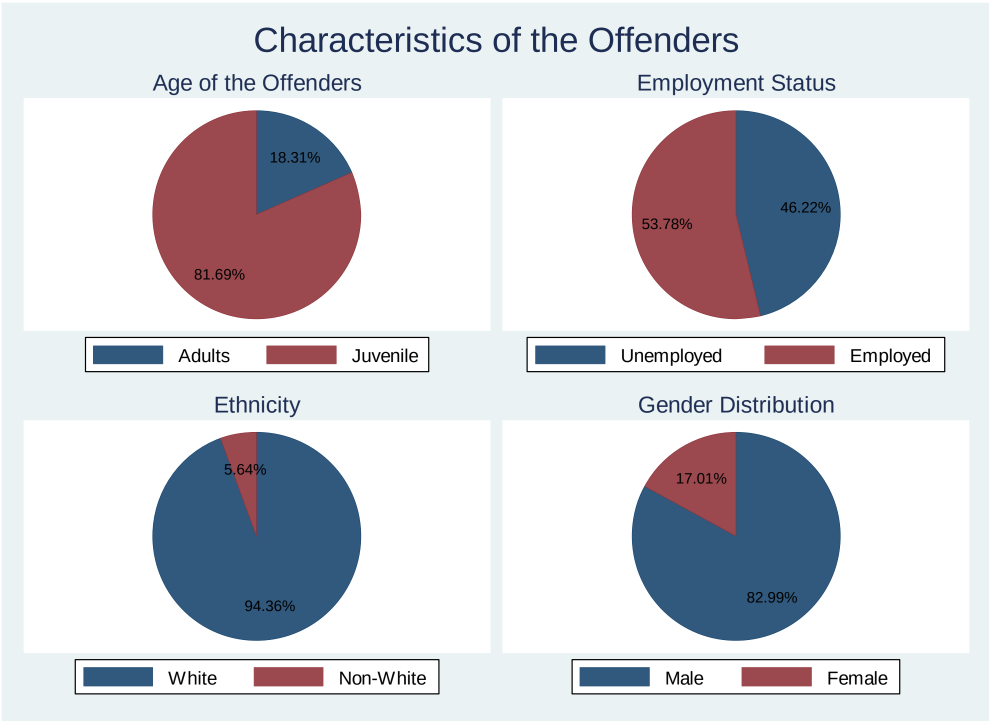
This framework shows that treatment effect estimation presents a missing data problem. It can be illustrated by decomposing ATE in terms of the known factuals and unknown counterfactuals. Inserting ATT and ATU equations in our last ATE equation (1) we get:

$$E(Y_i^1 - Y_i^0) = \Pr(T_i = 1)\ [E(Y_i^1 \mid T_i = 1) - E(Y_i^0 \mid T_i = 1)] + \Pr(T_i = 0)\ [E(Y_i^1 \mid T_i = 0) - E(Y_i^0 \mid T_i = 0)]$$

The unknown counterfactuals are $E(Y_i^0 \mid T_i = 1)$ which is the potential outcome if no treatment is received in the treated sample and $E(Y_i^1 \mid T_i = 0)$ which is the potential outcome of the treatment in untreated sample.

C.2 Characteristics of the Offenders for age, employment status, ethnicity and gender distributions, 2010 – 2014, Norfolk and Suffolk Police

Figure 13: Characteristics of the Offenders for age, employment status, ethnicity and gender distributions, 2010 – 2014, Norfolk and Suffolk Police



C.3 Descriptive Statistics – Male Only Sample

Table 34: Descriptive Statistics, Male Only Sample

Descriptive Statistics

Male Only Sample

Variable	Description
Reoffending	Police record of one more arrest after committing first offence (0 = no, 1 = yes)
Treatment	Receiving Community Resolution as police outcome (0 = no, 1 = yes)

		Mean							
		Unmatched		Matched				t-test	
		Treated	Control	Treated	Control	%bias reduction	%bias	t	p>|t|
Sociodemographic									
Ethnicity	0 = White, 1 = Non-White	0.06	0.08	0.06	0.04	46.5	4.3	0.75	0.46
Age at the first offence	Age at admission	23.9	29.2	23.9	23.8	99	0.4	0.06	0.95
Employment	0 = unemployed, 1 = employed	0.61	0.63	0.61	0.58	-23.62	5.7	0.86	0.39
Current crime									
Assault	0 = no, 1 = yes	0.24	0.2	0.24	0.23	78.5	2.1	0.31	0.76
Criminal Damage	0 = no, 1 = yes	0.15	0.09	0.15	0.14	80.3	3.9	0.55	0.58
Theft	0 = no, 1 = yes	0.29	0.17	0.29	0.3	96.5	-1	-0.14	0.89
Harassment	0 = no, 1 = yes	0.09	0.06	0.09	0.09	87	-1.6	-0.23	0.82

C.4 Descriptive Statistics – Employed Only Sample

Table 36: Descriptive Statistics – Employed Only Sample

Descriptive Statistics

Employed Only Sample

Variable	Description
Reoffending	Police record of one more arrest after committing first offence (0 = no, 1 = yes)
Treatment	Receiving Community Resolution as police outcome (0 = no, 1 = yes)

		Mean						t-test	
		Unmatched		Matched					
		Treated	Control	Treated	Control	%bias reduction	%bias	t	p>|t|
Sociodemographic									
Ethnicity	0 = White, 1 = Non-White	0.06	0.07	0.06	0.05	-1.5	2.2	0.32	0.75
Age at the first offence	Age at admission	22.3	28.7	22.3	22.53	99.3	0.3	0.05	0.96
Gender	0 = Male, 1 = Female	0.23	0.14	0.23	0.22	96.9	0.7	0.09	0.93
Current crime									
Assault	0 = no, 1 = yes	0.29	0.24	0.29	0.31	80.9	-2.5	-0.32	0.75
Criminal Damage	0 = no, 1 = yes	0.16	0.09	0.16	0.16	95.8	0.8	0.1	0.92
Theft	0 = no, 1 = yes	0.23	0.17	0.23	0.22	85.1	2.1	0.27	0.79
Harassment	0 = no, 1 = yes	0.1	0.06	0.1	0.1	75.5	-3	-0.37	0.71

C.5 Descriptive Statistics – Unemployed Only Sample

Table 37: Descriptive Statistics – Unemployed Only Sample

Descriptive Statistics

Unemployed Only Sample

Variable	Description
Reoffending	Police record of one more arrest after committing first offence (0 = no, 1 = yes)
Treatment	Receiving Community Resolution as police outcome (0 = no, 1 = yes)

		Mean						t-test	
		Unmatched		Matched					
		Treated	Control	Treated	Control	%bias reduction	%bias	t	p>|t|
Sociodemographic									
Ethnicity	0 = White, 1 = Non-White	0.03	0.08	0.03	0.02	91.8	1.8	0.28	0.78
Age at the first offence	Age at admission	27.2	30.5	27.2	27.4	92.8	-2	-0.23	0.82
Gender	0 = Male, 1 = Female	0.27	0.18	0.27	0.29	83.4	-3.8	-0.4	0.69
Current crime									
Assault	0 = no, 1 = yes	0.21	0.15	0.21	0.2	86.9	2.1	0.22	0.83
Criminal Damage	0 = no, 1 = yes	0.09	0.07	0.09	0.09	85.8	1.4	0.15	0.88
Theft	0 = no, 1 = yes	0.38	0.22	0.38	0.4	87.6	-4.4	-0.45	0.65
Harassment	0 = no, 1 = yes	0.09	0.06	0.09	0.08	61.1	4.6	0.49	0.62

C.6 Descriptive Statistics –Juvenile Only Sample

Table 38: Descriptive Statistics –Juvenile Only Sample

Descriptive Statistics

Juvenile Only Sample Variable	Description
Reoffending	Police record of one more arrest after committing first offence (0 = no, 1 = yes)
Treatment	Receiving Community Resolution as police outcome (0 = no, 1 = yes)

		Mean						t-test	
		Unmatched		Matched					
		Treated	Control	Treated	Control	%bias reduction	%bias	t	p>|t|
Sociodemographic									
Ethnicity	0 = White, 1 = Non-White	0.06	0.08	0.06	0.06	100	0	0	1
Employment	0 = Unemployed, 1 = Employed	0.76	0.77	0.76	0.76	100	0	0	1
Gender	0 = Male, 1 = Female	0.23	0.18	0.23	0.21	62.9	4.7	0.52	0.602
Current crime									
Assault	0 = no, 1 = yes	0.27	0.26	0.27	0.3	-84.5	-5.1	-0.57	0.57
Criminal Damage	0 = no, 1 = yes	0.18	0.17	0.18	0.17	19.4	1	0.11	0.91
Theft	0 = no, 1 = yes	0.22	0.18	0.22	0.22	100	0	0	1
Harassment	0 = no, 1 = yes	0.06	0.04	0.06	0.06	100	0	0	1

C.7 Descriptive Statistics –Adult Only Sample

Table 39: Descriptive Statistics –Adult Only Sample

Descriptive Statistics

Adult Only Sample

Variable	Description
Reoffending	Police record of one more arrest after committing first offence (0 = no, 1 = yes)
Treatment	Receiving Community Resolution as police outcome (0 = no, 1 = yes)

		Mean						t-test	
		Unmatched		Matched					
		Treated	Control	Treated	Control	%bias reduction	%bias	t	p>|t|
Sociodemographic									
Ethnicity	0 = White, 1 = Non-White	0.04	0.07	0.04	0.04	100	0	0	1
Employment	0 = Unemployed, 1 = Employed	0.46	0.59	0.46	0.46	100	0	0	1
Gender	0 = Male, 1 = Female	0.26	0.26	0.15	0.26	100	0	0	1
Current crime									
Assault	0 = no, 1 = yes	0.25	0.19	0.25	0.25	100	0	0	1
Criminal Damage	0 = no, 1 = yes	0.1	0.07	0.1	0.1	100	0	0	1
Theft	0 = no, 1 = yes	0.034	0.19	0.34	0.34	100	0	0	1
Harassment	0 = no, 1 = yes	0.12	0.06	0.12	0.12	100	0	0	1

C.8 Descriptive Statistics –Assault Offences Only Sample

Table 40: Descriptive Statistics –Assault Offences Only Sample

Descriptive Statistics

Assault Only

Variable	Description	Mean							
		Unmatched		Matched				t-test	
		Treated	Control	Treated	Control	%bias reduction	%bias	t	$p>\lvert t\rvert$
Reoffending	Police record of one more arrest after committing first offence (0 = no, 1 = yes)								
Treatment	Receiving Community Resolution as police outcome (0 = no, 1 = yes)								
Sociodemographic									
Ethnicity	0 = White, 1 = Non-White	0.06	0.06	0.06	0.05	-32.9	2.6	0.25	0.804
Employment	0 = Unemployed, 1 = Employed	0.67	0.72	0.67	0.68	87.41	-1.3	-0.12	0.91
Gender	0 = Male, 1 = Female	0.3	0.17	0.3	0.3	95.4	1.5	0.12	0.9
Age at the first offence	Age at admission	23.1	29.5	23.1	232.9	97.1	1.5	0.14	0.89

C.9 Descriptive Statistics –Theft Offences Only Sample

Table 41: Descriptive Statistics –Theft Offences Only Sample

Descriptive Statistics

Theft Only

Variable	Description
Reoffending	Police record of one more arrest after committing first offence (0 = no, 1 = yes)
Treatment	Receiving Community Resolution as police outcome (0 = no, 1 = yes)

		Mean						t-test	
		Unmatched		Matched					
		Treated	Control	Treated	Control	%bias reduction	%bias	t	$p>\lvert t\rvert$
Sociodemographic									
Ethnicity	0 = White, 1 = Non-White	0.03	0.05	0.03	0.04	33.4	-8.5	-0.85	0.4
Employment	0 = Unemployed, 1 = Employed	0.46	0.55	0.46	0.46	94	1.1	0.11	0.92
Gender	0 = Male, 1 = Female	0.24	0.24	0.24	0.2	-2159.1	9.1	0.89	0.37
Age at the first offence	Age at admission	27.1	30	27.1	26.6	83.1	3.7	0.33	0.74